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Master Thesis in Financial Economics

Quantitative Investment Strategies in LatAm Equity Markets: Challenging the Efficient Market Hypothesis (EMH)

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Abstract

Using LatAm data from 2000 to 2018, this research investigates asset pricing anomalies that have been found to generate outperformance globally. Specifically, we examine the Value, the Momentum, the Low Volatility, and the Quality anomaly in Brazil, Mexico, Chile, Peru, and Colombia. All anomalies are found to be profitable, but Value and Momentum are the strongest in these markets. Alternative definitions for the effects generate higher expected returns and lower standard deviations than the traditional ones. The performance of single-factor portfolios can be enhanced by combining two or more anomalies simultaneously, and the portfolio blending approach is the best method to multi-factor portfolio construction. We find that a dynamic asset allocation strategy, leveraged by the concept of Absolute Momentum, can significantly improve the Sharpe ratio of multi-factor portfolios and reduces the exposure to extremely adverse events. It also makes the distribution of monthly returns to be positively skewed. Finally, we show that single- and multi-factor portfolios may have long periods of bad performance, while a dynamic asset allocation strategy to multi-factor portfolios performs well in all business cycles.

JEL classification: G11; G12; G14; G15

Keywords: Emerging Markets; LatAm; Value; Momentum; Low Volatility; Quality; Risk Factors; Portfolio Blending Approach; Signal Blending Approach; GRS Test; Absolute Momentum

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1 Introduction

Eugene Fama (1970) developed a framework for describing the degree to which markets are efficient. In an efficient market, prices fully reflect all available information at any point in time. Therefore, from an asset management point of view, none investor could earn abnormal returns concerning the Market by making investment decisions based on available data as prices already reflect this information. As a result, a passive investment strategy that does not seek superior risk-adjusted returns is preferred over an active investment strategy due to lower transaction costs. In other words, in an efficient market, no one is expected to beat the Market consistently, and it is better to follow a passive approach to invest. Consequently, Market Efficiency assumes that market participants are rational economic beings, always acting in their self-interest and making optimal investment decisions.

However, in the 1990s, a new field of thinking known as Behavioral Finance started to challenge the basis upon the Efficient Market Hypothesis (EMH) was built, and the rationality of markets and investors. Behavioral Finance does not assume that people act rationally nor that the Market is efficient. Investors have behavioral biases that impact their financial decisions and, hence, markets are subject to these behavioral effects that may cause deviations from the efficiency hypothesis proposed by Eugene Fama. As more people started to question the EMH, a new research area in Behavioral Finance began to question whether investors acted rationally and in their best interests. If investors act emotionally and irrationally, this could cause asset prices to deviate systematically from their fundamental or efficient values. Therefore, markets could be beaten after all as irrational investors may allow inefficiencies to persist over time.

Evidence of market inefficiency was reported by Fama and French (1993) by the creation of a three-factor model to explain the cross-sectional variation in average stock returns. They show that the traditional one-factor model (i.e., the CAPM) is unable to explain the variation in stocks returns. It uses only the Market portfolio to explain any security excess returns. By having a closer look to the alphas generated by regressing the monthly returns for a Value and a Small-Cap (i.e., Size) strategy to the excess returns of the Market portfolio, they discover this risk factor is not enough to explain the variability of any security's excess returns. Alphas were far different from zero and statistically significant. Therefore, if an investor follows a pure Value strategy (buying/overweighting stocks with high book-to-market-ratio) or a small-cap strategy (buying/overweighting stocks with low market-cap), he would beat the Market. Consequently, Fama and French (1993) add two more explanatory variables to the CAPM (i.e., the Value and the Size risk factors) trying to explain any security's excess returns better and improve the explanatory power resulted from using only the Market Portfolio.

As a result, further research was taken in finding new anomalies that cannot be explained solely by the CAPM Model and the Fama-French Three-Factor Model. In 1993, Jegadeesh and Titman (1993) showed evidence of the Momentum anomaly and the implications for stock market efficiency. Recently, Fama and French (2015) also test profitability and investment factors and propose a new five-factor model. Although these findings are purely academic, many asset managers started to implement these strategies when managing portfolios. In the United States, AQR Capital Management offers a broad set of stylized mutual funds using single-style and multi-style strategies ranging from developed to developing equity markets. BlackRock has also created anomalies-based mutual funds selecting top one-third of stocks based on firm characteristics and rebalancing positions quarterly. In Europe, Robeco is the leading asset manager in offering quantitative-based strategies/mutual funds, also ranging from developed to developing equity and fixed income markets.

Although the use of quantitative investment strategies is broad among asset classes and markets, the development of these strategies is vague in LatAm. This situation may be due to liquidity and political risks international investors would face. On the other hand, local investors base their investment decisions in broad and diversified mandates (i.e., IPS) and the adoption of quantitative strategies lack experience and knowledge. Furthermore, local markets are not well-diversified, and sometimes, the number of issuers is limited to a few. However, there exist new regulations and developments to allow both institutional and retail investors to invest in a more integrated equity market. If consolidation persists, the use of quantitative strategies is prone to be a success.

Consequently, the present research pretends to find out whether quantitative investment strategies in LatAm equity markets can be used to challenge the Efficient Market Hypothesis (EMH). The findings of this study go beyond to merely be in a paper and will provide the basis to create and perform quantitative investment strategies from a portfolio management point of view. Single-style and multi-style strategies will be considered, and multi-style strategies will be tested to prove whether a better risk-adjusted performance could be obtained compared to single-style strategies. Finally, as the corresponding strategies are not always profitable (there are periods of disappointing performances), an Absolute Momentum strategy will be used to time the Market and, particularly, the factors. In this way, this thesis would assess whether asset allocation strategies can be used to improve the risk-adjusted performance of quantitative investment strategies.

There is no existing literature dedicated only to LatAm equities trying to document the performance of trading strategies based on different anomalies. Most available research has centered on the profitability of systematic strategies in Emerging Markets as a whole as it is more efficient to explore an entire asset class. Thus, this research is part of a considerable effort to study the behavior of equity markets in Latin America and creates contributions to the literature regarding Emerging Markets in strategies and methodologies that have not been tested so far. Our research can be regarded as complementary to Hart, Slagter, and Dijk (2003) who test the performance of Momentum, Value, Earnings Revisions, and Short-term and Long-term Mean Reversions in 32 emerging markets. They also form multi-factor portfolios based on various strategies by using a signal blending approach. Their results are significant for the difference portfolios, but for long-only single-factor portfolios, the alphas are weaker.

Our paper differs from Hart, Slagter, and Dijk (2003) and contributes to the existing literature in many ways. First, we construct systematic risk factors with LatAm fundamental and returns data and create the SMB, the HML, and the UMD factor to explain cross-sectional variation in all strategies by systematic risk factors. Thus, we show that Size, Book-to-Market Equity, and Momentum can explain the cross-section of stock returns in LatAm equity markets. Second, we confirm previous work on Value, Momentum, Low Volatility, and Quality and also consider various definitions for each anomaly. Thus, we are the first ones to use Operating Profit-to-Enterprise Value and Ebit-to-Enterprise Value as a definition of market valuation in LatAm.

Furthermore, we are also the only ones to apply a Quality Momentum strategy over the LatAm universe. Therefore, we show that the path of the past returns matters and creates a better risk-return relationship compared to Generic Momentum strategies. Third, we test the statistical significance of creating multi-factor strategies, and we are also the only ones to apply the two methodologies used to multi-factor portfolio construction in the LatAm universe by creating seven different multi-factor portfolios. Finally, and perhaps the most innovative attribute and contribution of this paper is the implementation of a dynamic asset allocation strategy to time multi-factor portfolios. We are the only ones to document the effectiveness of actively selecting multi-factor portfolios and investments in fixed income securities to improve the Sharpe ratio of multi-factor strategies in LatAm equities.

The remainder of this paper is structured as follows. Section 2 discusses all the existing literature relevant to this research. Section 3 and 4 deal with the hypothesis development to be proved throughout the paper and the description of the data used during the experimentation. Then, section 5 explains in detail all the methodology we use to report all the empirical evidence in the document. Later on, section 6 illustrates all the empirical evidence and results obtained for the single-factor and multi-factor strategies as well as for the dynamic asset allocation strategy, while section 7 perform a variety of tests to look at the reported strategies from different points of view so we can get a better understanding of the properties for each of them. Finally, Section 8 concludes the study.

2 Literature Review

2.1 The first asset pricing model: the CAPM

In early financial research, several authors investigate minimum-variance investing and the risk-return relationship. The work by Markowitz (1952) turns out to be perhaps one of the most influential in this field and set the fundamentals on which many modern theories rely on. Markowitz introduces a rule that states that an investor should hold a portfolio with a minimum variance and a maximum expected return. If an investor is always destined to hold such a portfolio, he must be a mean-variance optimizer and must have sufficient knowledge about returns and variances to compute his portfolio. Markowitz explains the concept of the "right kind" of diversification by stating that an investor does not merely have to increase the number of assets held, but must invest in assets with low correlation. Markowitz also introduces an efficient frontier for investors. This frontier shows optimal return-variance portfolios and states that stocks or portfolios not lying on this frontier are not efficient or optimal to hold.

Sharpe (1964) builds on Markowitz (1952) to introduce a model of investor behavior by coming up with utility levels and indifference curves that are specific to an individual investor. The more risk-averse an investor is, the more she needs to be rewarded in terms of expected return. Therefore, an investor chooses a set of investment opportunities that maximizes her utility. He also expresses the definition of a portfolio's expected return and standard deviation, and the implications of the correlation between two different assets into a portfolio's risk mathematically. Sharpe introduces the capital market line (CML) concept. The CML line implies that an investor may only achieve higher returns if she is willing to incur a higher amount of risk. Subsequently, he divides the risk of an individual security into two parts: a systematic part and an idiosyncratic part. The latter is considered diversifiable, but the systematic risk remains present even in efficient combinations. This distinction between systematic risk and idiosyncratic risk leads to the first asset pricing model in finance history: the Capital Asset Pricing Model (CAPM)[1].

According to Sharpe, those assets that have more sensitivity to the economic activity and hence more exposure to systematic risk should promise a higher expected return. Therefore, according to the CAPM, any asset's return would be solely the compensation for bearing systematic risk or the risk derived from changes in the economic activity. One of the most well-known critiques on the CAPM comes from Roll (1977). He casts doubt on the fact that the CAPM implies a perfectly well-diversified market portfolio. According to his opinion, such a portfolio does not exist. He also criticizes studies that use a proxy (e.g., S&P 500) for the market portfolio. Since these proxies contain fewer assets than there are available, the proxy might turn out to be inefficient while the real Market portfolio is mean-variance efficient. Consequently, the beta itself as a measure of risk would be misleading and would depend on the market portfolio used.

2.2 The emergence of new factors and anomalies

Since then, there has been a proliferation of CAPM-related research. However, the results do not always seem to be in line with each other. This fact encouraged researchers to believe that additional factors may influence assets' prices, setting up a new wave of financial literature that explored new effects whose performance could not be apparent by the CAPM. Perhaps the first evidence against the CAPM was documented by Haugen and Heins (1972) who show that more volatile funds exhibit lower average rates of return, and hence systematic risk does not generate any reward. They criticize previous studies supporting the CAPM by arguing that these suffered from selection bias as were conducted in a bullish market scenario and included only funds that were in existence throughout the entire realization of the experiment (i.e., survivorship bias). After correcting for these biases, they do not find evidence supporting the risk premium hypothesis nor that an increase in the expected return accompanies an increase in the risk of a stock. Therefore, Haugen and Heins (1972) lay the foundation to what it is known today as the low-volatility anomaly.

Basu (1977) examines the relationship between returns and price-to-earnings (P/E) ratios. His results indicate that P/E ratios are indicators of a stock's future performance. Portfolios

[1]It is worth mentioning here that the CAPM was introduced independently by Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966).

with low P/E ratios had superior returns than portfolios with high P/E ratios, and so being consistent with the claims of proponents of the price-ratio hypothesis. The methodology he employed helped to set the standard for empirical asset pricing and the discovery of new anomalies. Similar to Haugen and Heins (1972), he finds that portfolios with low market-β experience, on average, a higher rate of return compared to high-risk portfolios, bringing into the light once more the inconsistencies of the CAPM. This finding led him to think that either (*i*) the CAPM does not completely explain the risk-return relationship and that other risk factors were missing in the model to be well-specified, or that (*ii*) asset prices behavior were not consistent with the Efficient Market Hypothesis. Unsurprisingly, Basu is considered to be one of the precursors of the Value effect documented nowadays.

Other research studies regarding the validity of the CAPM started to build up. Litzenberger and Ramaswamy (1979) find a robust positive relationship between the expected return of stocks and dividend yields. However, the most prominent contradiction was given by Banz (1981). He finds that stocks of small firms, and thus a low market equity (ME), have risk-adjusted returns that are too high and stocks of big firms, and thus a high ME, have risk-adjusted returns that are too low. He names this phenomenon as the "size effect" and claims the findings are a piece of strong evidence that the CAPM is misspecified. Banz does not dare to say that equity market value was a risk factor *per se* that must be considered by the CAPM, but he humbly states it was an additional factor relevant for asset pricing that had just been found. He uses a double sort approach to create twenty-five portfolios sorting first on market equity value and then on market-β to prove that the size effect is not a proxy for systemic risk.

Rosenberg, Reid, and Lanstein (1985) find that buying stocks with high book-to-market equity ratios and selling stocks with low book-to-market equity ratios generates statistically significant abnormal returns, documenting a strong January effect in the performance of the strategy and arguing too that trading costs would not drain down the profitability. In the same paper, they also introduce a return reversal strategy aiming to buy stocks that have performed poorly and sell stocks that have performed well in the recent month, hoping the prior return performance to reverse back in the subsequent month. Compared to the Value strategy, the return reversal strategy delivers a higher significant abnormal return. However, as the portfolio turnover is higher for the implementation of the strategy, trading costs would make the strategy unattractive. They conclude that the findings of both strategies continue to challenge the efficient market hypothesis and indicate that there are still large potential profits to be made from valuation errors.

2.3 A new wave of asset pricing models

With all these contradictions in mind, Fama and French (1992) evaluate the influence of size and book-to-market ratio on expected returns. Their key results show that β does not help to explain the cross-sectional returns. When the experiment allows for the variation in β that is not related to size, they find that the relation between market-β and returns was falt. Furthermore, they find that stock returns are multidimensional. The first dimension is proxied by size, and the second is captured by the ratio of book equity to market equity (BE/ME). As a result, Fama and Frech (1993) develop a new asset pricing model that is considered by many as an expansion of the CAPM. This new model, the Fama-French Three-Factor Model, includes size (small minus big, SMB) and the book-to-market equity ratio (high minus low, HML) as the two new risk factors under the evidence that market-β is not sufficient enough to explain the cross-sectional returns.

The idea behind using SMB as a risk factor is that small-cap firms, in general, are riskier than large-cap firms. Small firms are less covered from analysts, so their prices update less often. Besides, small-cap stocks are often less traded, and their liquidity is lower. Therefore, investors would require a premium to compensate for the risk that they bear as a result of a widening bid-ask spread. On the other hand, the economic rationale to include HML as a risk factor is that companies whose stocks are perceived to be cheap (i.e., value bets) face a higher risk since their market value has decreased due to numerous negative reasons. The general belief is that a high book-to-market ratio implies that a company has no growth opportunities anymore. Fama and French (1992) show that companies with a high B/M ratio tend to have a lower earnings ratio and are thus persistently distressed. This fact would be in line with the "relative distress effect" developed by Chan and Chen (1991) which states that compensation would be required for bearing the risk of holding these stocks.

Critics to the Fama-French Three-Factor model came as it was the case for the ones drawn regarding the CAPM. One reason for them was given even by Fama and French themselves. In their paper, they state that the market equity works as a proxy for size and B/E as a proxy for Value. However, they do not give a theory of why it works. Several researchers took this as an occasion to conduct their studies. We have seen that there are still some anomalies that cannot be explained by the Fama-French Three-Factor Model. For instance, Kothari, Shanken, and Sloan (1995) insinuate that Fama-French did not consider a survivorship bias when conducting their study. Many companies that had low market equity and high book equity to market equity ratio may not have survived and are thus not included in the database. Consequently, they used a different database and found that BE/ME is weakly related to average stock returns. Contrarily to Fama and Frech (1993), they found that when using annual returns in the estimation of beta, there is a compensation for systematic risk.

Black (1993) and MacKinlay (1995) accuse Fama and French of data-snooping. Since they build their portfolios ex-post, it is more likely to find deviations. These deviations, however, are due to chance rather than to any model-inherent characteristics. They claim that if one tests the model on other markets different than the US market, then the market capitalization and B/M will no longer hold as a proxy for Size and Value. Particularly, Black (1993) states that Fama and French studied the size effect during the period since the Banz study was firstly published (i.e., 1981-1990). According to him, they did not find empirical evidence of the size effect in this period, but still claim that size helps to explain the cross-sectional variation in returns. Therefore, Black assures Fama and French published only the findings that support their conclusions leading to a serious problem of data mining. He gives credit to this fact as the reason why Fama and French did not provide any economic reason for a relation between Size and Value with expected returns.

In the same year as Fama-French publish their seminar paper, Jegadeesh and Titman (1993) would document the Momentum effect, one of the most challenging anomalies for traditional finance and the efficient market hypothesis. They show that a strategy that buys companies whose stocks have performed well in the past and sells companies whose stocks have performed poorly in the past delivers, on average, statistically significant abnormal returns that cannot be explained for systematic risk. They consider trading strategies with 3- to 12-months formation periods as well as 3- to 12-months holding periods, providing evidence that the most successful strategy selects stocks based on the performance of the previous 12 months and rebalances itself every quarter. They also introduce a model to determine the source of the performance of the strategy. The estimates of the model lead to the conclusion that Momentum profits may arise due to underreaction to firm-specific information. Therefore, they suggest that stock prices follow specific patterns and thus reject the EMH and its assumption that stock prices follow a random walk.

In a follow-up study, and using the results of Jegadeesh and Titman (1993), Carhart (1997) creates the UMD (up minus down) factor proxying the Momentum effect and introduces the Carhart Four-Factor Model to explain the expected returns for securities. This model extends the Fama-French Three-Factor model with the Momentum factor constructed as the return of a portfolio that goes long stocks in the top decile and shorts stocks in the bottom decile on companies sorted on the past 12 months performance. By using a data set of diversified equity funds, he shows that the Carhart Four-Factor model better explains the variation in the average cross-sectional returns of mutual funds compared to the CAPM. According to his findings, the CAPM's alphas for the top performance portfolios are positive, while the Carhart model's alphas are negative for the same sample. He shows that top performers (i.e., mutual funds) tend to have a higher exposure to Size and Momentum. However, it does not mean portfolio managers followed a Momentum strategy but, in contrast, that many mutual funds ended up holding last year's winners only by chance.

2.4 Asset pricing in the XXI century

As the Momentum factor enhanced particularly well the explanatory power of the Fama-French Three-Factor model, many researchers started to find new Momentum-related strategies to continue challenging the EMH and the latest asset pricing models. Blitz, Huij, and Martens (2011) show that traditional Momentum strategies are less stable and exhibit significant time-varying exposures to the Fama-French factors. Instead, a Momentum strategy that ranks a stock based on residual return in place of total return can double the Sharpe ratio by reducing at half the risk while keeping the strong return potential of the traditional strategy. Furthermore, Novy-Marx (2012) examines different Momentum windows other than the [12,3] from Jegadeesh and Titman (1993) and surprisingly find that the Momentum effect is not primarily driven by recent past [6,2] Momentum but by intermediate horizon past Momentum [12,7]. More formally expressed, the [12,7] horizon seem to drive Momentum more substantially than, for example, the [6,2] window. Possible explanations for the observed results, however, are currently not apparent and provide a significant challenge for future research.

On the other hand, Blitz and van Vliet (2007) retake the low-volatility effect documented by Haugen and Heins (1972) many years ago. They find the same compelling evidence that low-volatility stocks earn higher risk-adjusted returns using a more recent dataset that ranges from 1986 till 2006. In order to confirm the low-volatility effect, they use a 3-year volatility measure based on weekly returns to rank portfolios into deciles. Furthermore, their findings are not restricted to the US, as they also test the anomaly in regional and global stock markets. Specifically, they show that the Low Volatility effect has become stronger after 1995. Frazzini and Perdersen (2013) also find evidence that high-beta stocks are associated with low alpha. Therefore, they construct a Betting-Against-Beta (BAB) factor by creating a zero-beta portfolio which is long leveraged low-beta stocks and short high-beta stocks. They document that the BAB factor earns statistically significant risk-adjusted returns even after controlling for Market, Value, Size, Momentum, and Liquidity factors in the US and in international equity markets.

During the more recent years, many papers have found that factors which are commonly associated with Quality explain much of the stock returns. For instance, Novy-Marx (2013) finds that profitability has roughly the same power as book-to-market in predicting the cross-section of average returns. Moreover, George and Hwang (2010) show that returns are negatively related to financial distress intensity and leverage. Further factors that have been identified are high dividend growth (Campbell and Shiller (1988)), low earnings volatility (Wang and Williams (1994)), low accruals (Sloan (1996)), corporate reputation (Antunovich, Laster, and Mitnick (2000)), low share issuance (Baker and Wurgler (2002)), high growth (Mohanram (2005)), and high ROE and low investment (Chen, Novy-Marx, and Zhang (2011)).

Asness, Frazzini, and Perdersen (2013) were the first ones who put several of those risk factors into one single factor, called Quality minus Junk (QMJ). They split the Quality factors into three categories: safety, growth, and profitability. The authors find that by going long in stocks with a high-Quality score and by shorting stocks with a low-Quality score, a Sharpe ratio above one after controlling for its other factor exposures can be achieved. Their results suggest that Quality stocks are being underpriced and Junk stocks overpriced or that Quality stocks are being riskier than Junk stocks. However, they state that high-Quality stocks do not appear to be riskier. Therefore a risk-based explanation does not seem to hold in this framework. At this point, the returns to high Quality must be either an anomaly or caused by an underlying risk factor that has yet to be identified. More importantly, they find that today's high-Quality stocks continue to keep their condition five to ten years into the future.

In light of the new Quality factors documented so far, the Fama-French Three-Factor model seemed to fail in explaining much of the variation in expected returns in these anomalies, mainly the cross-sectional returns related to profitability and investment. Consequently, Fama and French (2015) extended their latest factor model with two additional factors, namely RMW (robust minus weak) and CMA (conservative minus aggressive). RMW represents a portfolio which is long in companies with high profitability and short in companies with low profitability. Meanwhile, CMA represents a diversified portfolio with long positions in firms with low investments and short positions in firms with high investments. Fama and French demonstrate that the five-factor model performs better in explaining the cross-sectional variation in returns compared to the three-factor model. However, by using the methodology developed by Gibbons, Ross, and Shanken (1989), they confirm that the five-factor model is an incomplete description of the expected returns. Finally, Fama and French conclude that their original HML factor is redundant when RMW and CMA are considered.

2.5 Empirical evidence in emerging markets and latam

The research of all these anomalies have been focused on the developed world (i.e., the US, Europe, and Japan) where markets are more liquid and transparent; investors can have better access to fundamental data and transaction costs are much lower. However, the research in these markets has been expanding in the last couple of years. Claessens, Dasgupta, and Glen (1998) were the first ones to start exploring the effects of certain anomalies in emerging markets. They find that, in addition to Market-β, size, trading volume, dividend yield, and earnings/price ratios are also good candidates to explain the cross-sectional variation in average returns in 18 emerging markets. Rouwenhorst (1999) also finds that factors that have been dominating average excess returns in developed markets are similar to those dominating emerging markets' returns. Notably, he documents that emerging markets stocks also exhibit a Momentum, a size, and a Value effect, but there is no empirical evidence that Market-β is associated with average returns.

Barry, Goldreyer, Lockwood, and Rodriguez (2002) perform a robustness check for the size and the Value effect in emerging markets when extreme returns are removed. They report evidence of the Value and the Size effect in 35 emerging markets countries. That is, Value stocks outperform Growth stocks, and large-cap firms underperform small-cap firms. Hart, Slater, and Dijk (2003) continue expanding the evidence of anomalies in emerging markets. They find that Value, Momentum, and Earnings Revision strategies generate substantial excess returns in emerging markets. They also find that combining Value, Momentum, and Earnings Revisions into one multi-factor portfolio improve the performance of single-factor portfolios. Finally, they demonstrate that institutional investor could successfully implement the strategies when liquidity and transaction cost issues are taken into account. The research to LatAm equity markets only has been scarce as this region is just a small portion of the global economy and the global equity market. The only documented research focused entirely to LatAm equities was published by Li and Sanchez (2014). They test the implementation of Momentum and Value in Brazil, Mexico, Chile, Peru, and Colombia, and also the effects of creating a joint strategy by selecting individual stocks with exposures to these effects simultaneously. They find that by combining Value and Momentum, an investor could potentially earn abnormal excess returns compared to a broad market benchmark index.

3 Hypothesis Development

Hypothesis 1: Size, book-to-market equity, and Momentum can explain the cross-section of stock returns in LatAm equity markets.

Fama and French (1992) show that Size and Value characteristics can explain the cross-sectional returns in the US equity market. They create a Size and Value factor by taking the difference in returns of a portfolio consisting of long positions in stocks with favorable characteristics and a portfolio consisting of short positions of stocks with unfavorable characteristics. Later on and taking the evidence of Jegadeesh and Titman (1993), Carhart (1997) created a Momentum factor with the aim of explaining the persistence in equity mutual funds' risk-adjusted returns. Finally, Fama and French (2015) extend their original three-factor model by incorporating two more factors, profitability and investment, to better capture the average cross-sectional returns in US equity markets. Since then, these factors have been used to evaluate investments strategies and portfolio performance, but more importantly to measure abnormal risk-adjusted returns.

Proponents of the Efficient Market Hypotheses (EMH) argue that in an efficient market, nobody could earn consistently abnormal returns. Therefore, when assessing an investment strategy, the model employed is crucial for evaluating the performance attractiveness and whether the strategy could challenge the EMH. A misspecified model could always be in favor of an investment strategy or portfolio manager. Consequently, the Fama-French five-factor model has received many critics. For instance, Blitz, Hanauer, Vidojevic, and Vliet (2016) bring into light five concerns with regard to the five-factor model and Hou, Mo, Xue, and Zhang (2018) demonstrate how the $q-$factor and the q^5 models[2] largely subsume the Fama-French 5 factors premiums.

Despite the goal of this research is not to show which factor model is the best in explaining the cross-sectional returns in LatAm equity markets; it is crucial to use one that helps to assess the strategies considered throughout this study. As a result, we want to show that a Size, a Value, and a Momentum effect exist in LatAm equity markets and that these can serve as a foundation to create different factor models to determine the attractiveness of

[2]The $q-$factor model was developed by Hou, Xue, and Zhang (2015) and includes a market factor, a size factor, an investment factor, and a profitability factor. The investment factor is constructed by forming portfolios based on the investment-to-assets ratio; while the profitability factor is constructed by creating portfolios based on the ROE. The q^5 factor model, developed by Hou, Mo, Xue, and Zhang (2017), augments the $q-$factor model with a growth factor which is constructed by forming portfolios based on the expected one-year-ahead investment-to-assets change.

different strategies in the targeted market. The monthly factor premiums can be accessed via Kenneth French's data library. These premiums include only the whole US universe. Therefore, we genuinely believe it is not convenient to employ the available factors as they are not represented within our sample data (i.e., LatAm equities).

Hypothesis 2: Value, Momentum, Low-Volatility and Quality sorted portfolios can generate abnormal excess returns after controlling for systematic risks factors in LatAm equity markets.

Many anomalies have been documented in academic literature. Nowadays, the most well known are the Value effect, the Momentum effect, the Low-Volatility effect, and the Quality effect. Haugen and Heins (1972) show empirical evidence of the Low Volatility anomaly demonstrating that stock portfolios with lower variance in monthly returns experience higher average returns compared to riskier portfolios. This idea was further tested by Blitz and van Vliet (2007) who show that large-cap stocks with Low Volatility earn high risk-adjusted returns. Basu (1977) was the first to report the Value anomaly showing that companies with low P/E ratios outperform companies with high P/E ratios even after controlling for risk. Meanwhile, Levy (1967) document a Momentum effect by using relative strength for investment selection, highlighting the positive correlation between past performance in portfolios and future performance in portfolios.

Jegadeesh and Titman (1993) further develop Levy's idea and notify that stocks that have performed well in the past relative to other similar assets continue to doing well in the future. Finally, Asness, Frazzini, and Pedersen (2013) were the first ones who put several Quality risk factors into one single strategy to generate superior risk-adjusted returns by buying high-Quality companies and selling low-Quality or Junk companies. All these studies are applied to the US universe only, and in some cases, the targeted market is the global equity market. Due to liquidity concerns and political risks, LatAm equity markets have not been researched extensively, and empirical evidence of well-known anomalies is lacking. Therefore, this research pretends to document evidence of a Value effect, a Momentum effect, a low-volatility effect, and a Quality effect in LatAm equity markets.

Hypothesis 3: Multi-factor portfolios can significantly improve the performance of single-factor portfolios due to diversification benefits in LatAm equity markets.

Dimson, Marsh, and Staunton (2017) highlight the variability in the performance of different risk factor premiums across the US and the UK since the financial crisis. Despite the spanning period of the study is too short of drawing meaningful conclusions, it is decent evidence of one of the headaches of factor investing: risk premiums are not stable over time. The diversification among factors and the implementation of multi-factor strategies have been the solution to this problem. For instance, Blitz and Vidojevic (2018) show that single-factor portfolios are a sub-optimal solution to investing as individual securities within a particular factor may have negative exposures to other factors. They showed than by wisely selecting individual stocks with positive exposures to many factors (i.e., a multi-factor equity portfolio), an investor could earn higher returns.

The corporate bond market has also been subject to the implementation of multi-factor strategies. Houweling and van Zundert (2014) show that an equally-weighted multi-factor portfolio delivers a lower tracking error and a higher information ratio than individual long-only factor portfolios. They also report that blending corporate debt and equity factors is an efficient strategic asset allocation choice to investors. Israel, Palhares, and Richardson (2016) also demonstrate that a portfolio that combines Carry, Defensive, Momentum, and Value characteristics delivers a higher Sharpe ratio, suggesting that the different factors are weakly correlated. Consequently, this research seeks to contribute to the current literature of multi-factor strategies by documenting how different combination of factors contribute to improving the risk-return trade-off of single-factor portfolios in LatAm equity markets.

Hypothesis 4: A signal blending approach to multi-factor portfolio construction delivers better risk-adjusted returns compared to the portfolio blending approach.

There has been much debate on how to create multi-factor portfolios given the poor performance some single factors may experience through time. The two most known approaches are the portfolio blending approach and the signal/ranking blending approach. Many practitioners and researchers favor the former as it is more optimal to select individual stocks with the desired and integrated factor exposures by reducing the turnover and transaction costs simultaneously. For instance, Clarke, de Silva, and Thorley (2016) employ an exciting approach to show the best way to combine different factors. They report that a combination of different factors by selecting individual securities using a score/ranking system obtains a higher Sharpe ratio improvement than merely employing an equally-weighted combination of four-factor portfolios. Fitzgibbons, Friedman, Pomorski, and Serban (2016) find similar results in favor of the integrated approach compared to the portfolio mix by showing that the latter increases the returns per unit of risk and improves the short-side of multi-factor portfolios by not holding stocks with poor negative style exposures.

However, Leippold and Rueegg (2017) contradict previous evidence favoring the signal-based approach versus the portfolio-based approach and document that the bottom-up approach to multi-factor portfolio construction is optimal in only a few combinations of strategies. They show that when applying more robust statistical tests and using a more extended period, the difference in performance among the two approaches is not statistically significant. Ghayur, Heaney, and Platt (2016) also find mixed results when applying both methodologies. By analyzing the combination of two, three and four different factors (i.e., Value, Momentum, Quality, and Low Volatility), they come to the conclusion that a signal blending approach produces higher information ratios across global equity markets at a high level of factor exposures; while the portfolio blending approach is superior for low and moderate levels of factor exposures. Consequently, this research tries to determine the difference in performance among the two approaches and brings new evidence into which of the two methodologies is the best when merging two or more strategies in LatAm equity markets.

Hypothesis 5: Absolute Momentum can be used as an effective dynamic asset allocation strategy to the timing of multi-factor portfolios.

Recently, Momentum strategies have been applied not only to generate abnormal excess returns in a stock-picking approach but also in an asset allocation framework. Antonacci (2012) introduces an innovative way to select between equities and fixed income securities actively. He uses the excess returns of equities over the past twelve months to set long/short positions in equities and Treasury bills when the cumulative absolute Momentum is positive or negative. He shows that trend-following absolute Momentum reduces volatility and drawdowns significantly while taking advantage of Momentum persistence. Georgopoulou and Wang (2016) also find that time-series Momentum is strong in developed and emerging markets equities. They evaluate different look-back periods and find that time-series Momentum is stronger for the first twelve months, and in emerging markets, the effect is steadier. Thereupon, this research also pretends to determine whether the use of time-series Absolute Momentum can be used as an active asset allocation strategy by selectively having exposure to multi-factor portfolios and fixed-income securities.

4 Data

We use monthly total return data of all public companies from five different countries in Latin America from January 2000 to December 2018. Holding-period returns are calculated at the end of each month for every individual stock using closing prices, adjusted for possibly stock related events such as dividend payments or stock splits. As each country has its local currency, assessing different strategies by country makes the analysis cumbersome and brings under diversification problems to our data. Therefore, local currency returns are then converted to USD returns using the spot USD exchange rates (USDBRL, USDMXN, USDCLP, USDPEN, and USDCOP) to ensure each company returns are comparable and denominated in the same currency. The countries that are represented in this analysis are Brazil (BR), Mexico (MX), Chile (CI), Peru (PE) and Colombia (CO). Our benchmark portfolio is the MSCI Emerging Markets Latin America Index[3] which captures large and mid-cap firms in five countries in Latin America. This index covers around 85% of the market capitalization in each country. Consequently, it serves as a good proxy for passive investors wanting to have exposure to the researched equity markets.

The decision to start analyzing all strategies from January 2000 to December 2018 is not arbitrarily. Figure 12 in the Appendix shows the evolution of the total number of companies downloaded from Bloomberg in our investment universe with one month of return, twelve months of returns, and thirty-six months of returns. In January 1992, the number of companies available to be purchased were lower than 50 but started to increase rapidly till the end of the 1990s. Meanwhile, Mexico accounted for the most percentage of public companies, as shown in Figure 13. Chile and Brazil started to gain leadership after 1995. However, the number of companies available was still low. As this paper tries to bring into light empirical evidence of the profitability of diversified trading strategies in LatAm, the number of companies to be obtained should be critical. Therefore, if we take into account possible diversification problems, then the implementation of factor portfolios would generate undesired results. Although many researchers and practitioners argue that the number of stocks an investor should have in his portfolio to be well-diversified is close to 30, we prefer to be conservative and require a minimum number of 25 based on the number of companies with at least twelve months of past return data as some anomalies such as the Momentum effect requires it. This fact leads to concentrate on the implementation of systematic investment strategies in LatAm from January 2000 to December 2018.

[3] EM Latin America countries included in the index are Brazil, Chile, Colombia, Mexico, and Peru.

Figure 1 shows the historical performance across equity markets in this research spanning from January 2000 to December 2018. In the last three decades, LatAm equity markets have been hit by various macroeconomic shocks. The shaded areas in Figure 1 show periods of recessions and macroeconomic shocks relevant to the region. At the beginning of the sample period, the 2001 recession in the United States caused by a boom and subsequent bust in the dot-com firms was accompanied by the default of Argentina's sovereign debt. Next, the subprime mortgage crisis led to the collapse of the US housing bubble and a global financial crisis that affected the economies in LatAm. Finally, the recent drop in commodities' prices slowed down economic growth in South America and Mexico, with many governments cutting planned spending. The occurrence of various regimes during the sample period helps to assess the strategies in different economic environments, which makes the analysis much more salient. In terms of performance, Colombia and Peru have exhibited the best behavior during this period followed by Chile, Mexico, and finally Brazil.

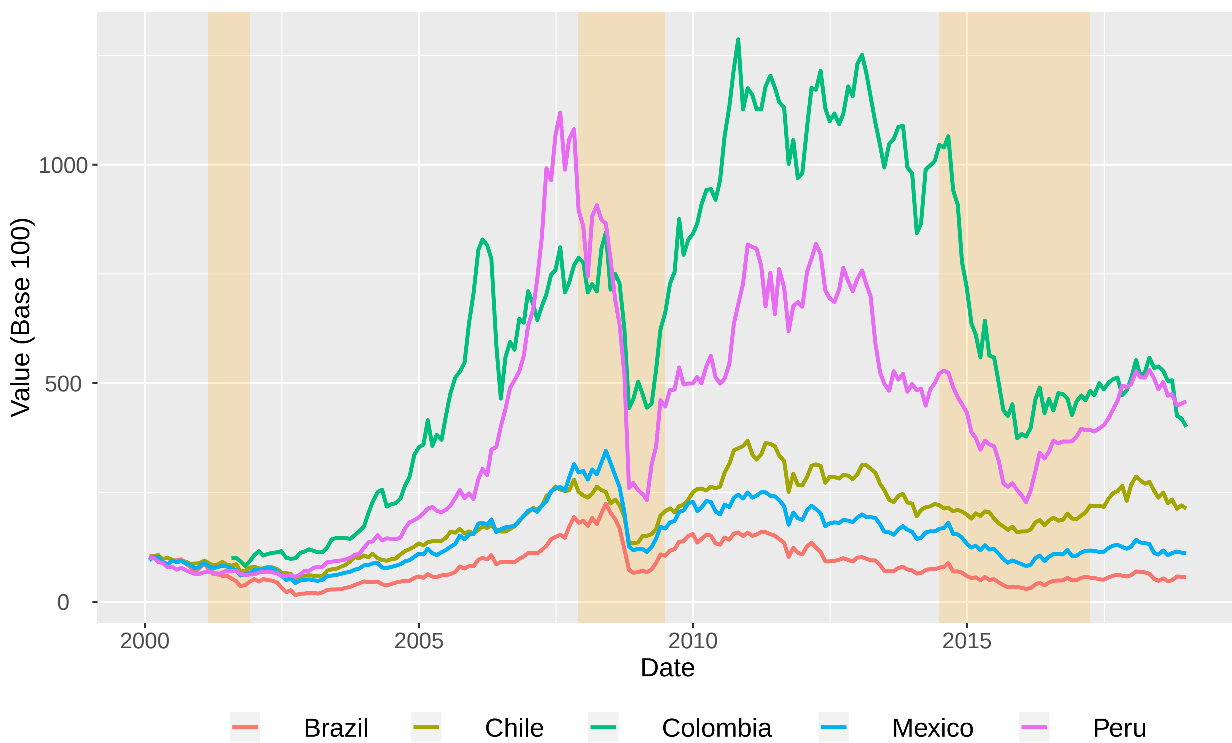

Figure 1: Historical performance across LatAm equity markets. This figure shows the individual performance by taking the most representative equity market for each country. For Brazil, Chile, Colombia, Mexico, and Peru the corresponding market indexes are BOVESPA, IPSA, COLCAP, MEXBOL, and SP/BVL, respectively. The shaded areas refer to periods of recessions and macroeconomic shocks relevant to the region.

We merge all public companies from two databases: Compustat Global and Bloomberg. We get all public companies under the codes BRL, MXN, CLP, PEN, and COP from Compustat Global, which includes fundamentals and stock prices for all publicly traded companies going back to the 1980s in more than 80 countries around the Globe. Compustat Global stores companies' data that have active market activity measured through prices, volume, and turnover. In this way, we guarantee that all publicly traded companies are included in our data sample. From Bloomberg, we extract all market indexes' constituents manually at every rebalancing date from the 1Q2000 to the 4Q2018, and we contrast this sample with Compustat Global's universe. It helps to include all public companies that were acquired or merged or filled for bankruptcy and validates any company that is lacking for some dataset individually, eliminating any bias that a particular source could bring to our research. Therefore, the sample is survivorship-bias free as whenever a firm defaults or is acquired/merged, the returns of its stocks are based on their final traded price.

However, as liquidity is a common problem in LatAm equity markets, a liquidity filter was applied. For all stocks resulted in the Compustat Global and Bloomberg merge, we perform a rolling-window average daily trading volume (ADTV) over three months by using the following formula:

$$ADTV_{it} = \frac{\sum_{t=1}^{60} \text{USD daily trading volume}_{it}}{60} \tag{1}$$

If a firm's ADTV over the entire sample period is lower than USD30,000 then it is dropped. A low value indicates that the stock cannot be traded easily. The three-month rolling-window is chosen based on the notion that most equity market indexes are rebalanced quarterly. After applying the screening, the final data sample includes 614 companies with over 100,000 return-month observations across the five selected countries.

Table I displays how the firms in our sample distribute over different countries and industries. Panel A illustrates that Brazil represents 31.9% in our sample. Mexico and Chile follow with 23.8% and 20.7%, respectively. Colombia makes up the smallest portion of the total sample with only 53 constituents. For the industries, Panel B shows that the financial and consumer, non-cyclical sector dominate with 18.9% and 17.1% of the total sample, followed by basic materials (13.7%), consumer, cyclical (13.5%), industrial (13%), and communications (8.7%). As expected, the technology sector constitutes a small share of the total sample with merely three firms. Panel C and D show that each country has at least one stock in each industry, which indicates that there are excellent diversification benefits in the sample and that all countries are well industrially diversified. However, specific patterns in industry concentration are evident in LatAm equity markets. For instance, all countries have reasonably high weights in the financial industry, but Brazil also has a high concentration of firms in the consumer, non-cyclical, and basic materials industry. Mexico, Chile, and Colombia depend significantly from the industrial and consumer, non-cyclical sector while Peru's most representative industry is the mining and processing of raw materials.

Table II gives the performance statistics of the monthly percentage mean and standard deviation using both equal-weights (EW) and value-weights (VW)[4] returns in LatAm equity markets. The table shows that country and industry returns vary significantly and the variation in average returns and return volatility is higher among industries than in countries. The difference in EW and VW returns suggests that small-cap firms tend to depict a lower expected return compared to large-cap companies across both the country and the industry sample. On a value-weighted basis, Colombia, Brazil, and Mexico are the countries with above-average returns, while Chile is below the average. However, the difference is not material, and all countries' returns behave alike. Brazil and Peru are the riskiest equity markets as measured by their standard deviations, while Chile and Mexico possess the lowest returns range. For the VW industry mean returns, the highest average returns are found in the financial and basic materials sectors and the lowest and negative in the energy and technology sector. The riskiest industry is the energy industry perhaps affected by the recent drop in commodity prices seen during the sample period, while the consumer, non-cyclical, industrial, utilities, and consumer, cyclical sectors are the less volatile in the sample.

Figure 2 shows the Pearson correlation matrices by country and industry and using both equally-weighted and value-weighted returns. Overall, value-weighted return correlations are lower compared to equally-weighted return correlations. Judging from the value-weighted country returns, the highest correlation among countries is 0.68 (Chile and Brazil), while the lowest is 0.28 (Colombia and Peru). These figures indicate that although correlations are not negative as equity markets are affected by the same systemic risk factors, some diversification benefits can be achieved by simultaneously investing in across LatAm firms. Industry return correlations are higher mainly among cyclical industries (Financial, Consumer, Cyclical, and Industrial) and lower in defensive sectors (Utilities and Energy). These results indicate that it is better to diversify on a country basis that by doing stock picking through industries.

[4]We use each firm's market capitalization in US dollars to calculate the value-weighted returns.

Table I
Country and Industry Composition

This table gives the number of companies included in the total sample for each country and industry. There are 614 firms spread across five different equity markets (Brazil, Mexico, Chile, Peru, and Colombia) and ten different industries (Financial, Consumer Non-cyclical, Basic Materials, Consumer Cyclical, Industrial, Utilities, Communications, Energy, Diversified and Technology). Each company is classified into industry groups according to the Global Industry Classification Standard (GICS) methodology. Each firm is assigned to a sub-industry according to its principal business activity. Panel A and B show the number of stocks included in the total sample and the percentage of the total number of firms for each country and industry. Panel C gives for each country the number of stocks included in the total sample by industry. Panel D gives the weights of the stocks included in the total sample by country and industry.

Panel A: By country (number and percentage of total)			
Brazil	BR	196	31.92%
Mexico	MX	146	23.78%
Chile	CI	127	20.68%
Peru	PE	92	14.98%
Colombia	CO	53	8.63%
Total		614	100.00%

Panel B: By industry (number and percentage of total)			
Financial	FI	116	18.89%
Consumer, Non-cyclical	CN	105	17.10%
Basic Materials	BM	84	13.68%
Consumer, Cyclical	CC	83	13.52%
Industrial	IN	80	13.03%
Utilities	UT	56	9.12%
Communications	CS	53	8.63%
Energy	EN	20	3.26%
Diversified	DI	14	2.28%
Technology	TE	3	0.49%
Total		614	100.00%

Panel C: Number of stocks by country and indudtry

	FI	CN	BM	CC	IN	UT	CS	EN	DI	TE	Total
Brazil	28	28	29	27	17	28	26	8	4	1	196
Mexico	31	30	12	28	25	2	13	1	4	0	146
Chile	25	27	12	15	20	17	4	2	4	1	127
Peru	16	15	29	7	8	4	7	4	1	1	92
Colombia	16	5	2	6	10	5	3	6	1	0	53
Total	116	105	84	83	80	56	53	20	14	3	614

Panel D: Weights of country/industry (in percentage)

	FI	CN	BM	CC	IN	UT	CS	EN	DI	TE	Total
Brazil	4.56	4.56	4.72	4.40	2.77	4.56	4.23	1.30	0.65	0.16	31.92
Mexico	5.05	4.89	1.95	4.56	4.04	0.33	2.12	0.16	0.65	0.00	23.78
Chile	4.07	4.40	1.95	2.44	3.26	2.77	0.65	0.33	0.65	0.16	20.68
Peru	2.61	2.44	4.72	1.14	1.30	0.65	1.14	0.65	0.16	0.16	14.98
Colombia	2.61	0.81	0.33	0.98	1.63	0.81	0.49	0.81	0.16	0.00	8.63
Total	18.89	17.10	13.68	13.52	13.03	9.12	8.63	3.26	2.28	0.49	100.00

Table II
Summary of Performance Statistics by Country and Industry

This table gives the performance statistics using equal-weights (EW) and value-weights (VW) monthly returns. All returns are in US dollars and expressed in percent per month. Panel A exhibits the mean, the standard deviation, the minimum, and the maximum of the EW and VW monthly returns by country. Panel B exhibits the mean, the standard deviation, the minimum, and the maximum of the EW and VW monthly returns by industry. Panel C exhibits the mean, the standard deviation, the minimum, and the maximum of the currency return. The currency return is the change in the exchange rate of a particular country concerning the US dollar. A positive value is indicative of an appreciation of the dollar against the local currency.

Panel A: By country (in percentage)

Country	Equally-Weighted Returns				Value-Weighted Returns			
	Mean	St. Dev	Min	Max	Mean	St. Dev	Min	Max
BR	0.42	9.83	-39.67	26.39	0.92	10.48	-57.02	26.52
MX	0.28	6.34	-41.50	16.20	0.86	6.39	-34.27	15.25
CI	0.42	5.97	-30.48	15.71	0.66	5.83	-27.53	18.29
PE	0.80	6.90	-40.21	25.73	0.79	8.43	-29.07	28.91
CO	0.72	7.52	-44.14	18.27	1.31	7.52	-29.26	19.03
Total	0.47	6.40	-37.08	17.36	0.98	7.31	-35.08	22.10

Panel B: By industry (in percentage)

Industry	Equally-Weighted Returns				Value-Weighted Returns			
	Mean	St. Dev	Min	Max	Mean	St. Dev	Min	Max
FI	0.65	6.18	-34.45	17.06	1.27	8.12	-35.16	21.18
CN	0.60	5.84	-36.27	19.27	0.97	5.96	-27.98	16.53
BM	0.61	8.22	-47.57	23.94	1.30	8.66	-37.88	23.50
CC	0.36	7.57	-43.68	26.25	1.03	6.78	-36.73	19.31
IN	0.29	6.39	-39.75	16.24	0,78	6.48	-36.11	17.31
UT	0.63	6.92	-25.40	24.19	0.79	6.48	-36.11	17.31
CS	-0.19	7.66	-30.54	19.46	1.25	9.01	-57.99	36.24
EN	0.84	13.27	-34.92	158.05	0.51	11.32	-48.10	36.28
DI	0.52	7.24	-36.68	17.75	0.95	7.41	-33.73	16.68
TE	-1.68	14.80	-75.04	52.44	-0.29	9.43	-43.63	26.11
Total	0.47	6.40	-37.08	17.36	0.98	7.31	-35.08	22.10

Panel C: Currency Returns (in percentage)

Country	Equally-Weighted Returns			
	Mean	St. Dev	Min	Max
BR	0.34	4.97	-14.14	21.83
MX	0.32	3.05	-7.36	15.92
CI	0.12	3.31	-6.79	19.46
PE	-0.02	1.42	-6.13	4.88
CO	0.24	3.67	-10.56	12.16

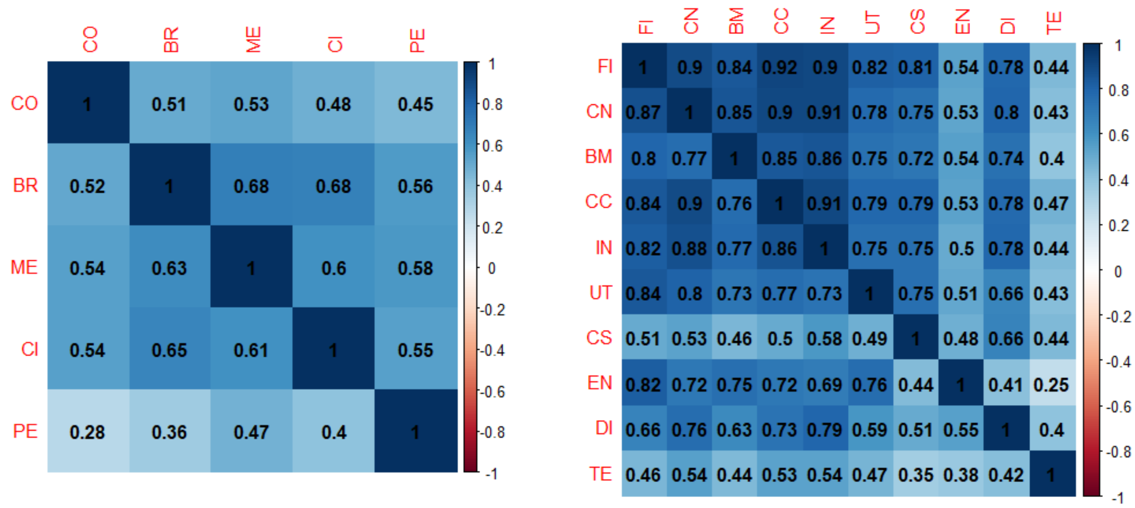

Figure 2
Correlation matrix by country and industry. This figure shows the Pearson correlation matrices by country and industry. The coefficients above the diagonal attribute to the equally-weighted returns and below the diagonal to the value-weighted returns. The intensity of the color refers to how strong the relationship between the two variables is.

5 Methodology

5.1 Portfolio analysis approach

We use the portfolio analysis approach described in Bali, Engle, and Murray (2015) as the statistical methodology to examine the cross-sectional relation between two or more variables into future stock returns. The idea is to create portfolios (i.e., deciles, quantiles, or quartiles) of stocks that have different levels of the characteristic(s) that are aimed to predict future returns. This methodology is one of the most used in empirical asset pricing as it has the advantage that none assumption is needed about the distribution of returns and the variables used to predict future behavior. Therefore, the historical data itself determines the distribution of the variables and returns. However, this approach is difficult to control when a large number of variables are used. In order to exemplify the portfolio analysis approach, assume we are interested in disentangling the effect of variable X into future stock returns.

The first step is to calculate the breakpoints that will be used to group firms into the different portfolios according to the values that each company has of variable X. Thus, firms that have values below the first breakpoint will be placed into the first portfolio. Then, companies with values of the variable X that are between the first and the second breakpoint will be added to the second portfolio. This process is continued up to the portfolio n_p and using several breakpoints equal to $n_p - 1$. Therefore, the formed portfolios and breakpoints are constant for all periods. The number of portfolios and breakpoints[5] will vary according to the sample's characteristics. The idea behind this approach is to form diversified portfolios that genuinely reflect the cross-sectional relation between variable X and future returns. Consequently, choosing an appropriate number of portfolios is an essential decision in portfolio analysis.

The second step in the portfolio analysis approach is to create the portfolios with the corresponding firms according to the breakpoints. Each time period t, all companies with values on the variable X that are less than the first breakpoint, $B_{1,t}$, are placed in the first portfolio, $P_{1,t}$. The second portfolio, $P_{2,t}$, contains firms with values on the variable X greater than the first breakpoint, $B_{1,t}$, but lower than or equal to the second breakpoint, $B_{2,t}$. This process is carried out until the last portfolio, $P_{n,t}$, includes companies i during time period t with values on the variable X greater than or equal to the last breakpoint, $B_{n,t-1}$. Therefore, we have

$$P_{n,t} = \{i | B_{n,t-1} \leq X_{i,t} \leq B_{n,t}\} \tag{2}$$

It is worth mentioning here that if a given firm has a value of the variable X during period t that is equal to two different breakpoints, then the company is included in both portfolios.

Having calculated the breakpoints and formed the portfolios, the next step is to compute the returns for each of the portfolios at each period t. The common practice is to calculate equally-weighted (EW) returns over each portfolio, $P_{n,t}$. This methodology gives the same weights to each firm as follows:

$$W_{i,t}^{E} = \frac{1}{N} \tag{3}$$

where $W_{i,t}^{E}$ is the weight allocated to company i in time period t, and N is the total number of firms for each portfolio, $P_{n,t}$. Therefore, the average return for portfolio n in time period

[5]Often breakpoints are calculated using only a subset of the sample. For instance, in the United States, it is usual to evidence portfolios formed on breakpoints on stocks that trade exclusively on the NYSE. For this research, breakpoints are created using all LatAm firms in the sample.

t is given by the following expression:

$$\overline{R}_{n,t}^{E} = \frac{\sum_{i \in P_{n,t}} W_{i,t}^{E} R_{i,t}}{\sum_{i \in P_{n,t}} W_{i,t}^{E}} \tag{4}$$

One advantage of using equal weights, $W_{i,t}^{E}$, is that a size tilt is implied in each portfolio, $P_{n,t}$. Thus, equally-weighted portfolios may benefit indirectly from the size anomaly. However, they might be rebalanced periodically, as changes in asset's prices may deviate firms' weights from equal weights. As a solution, it is better to consider firms within each portfolio by using the value of some other variable such as the market capitalization to compute a value-weighted return, $\overline{R}_{n,t}^{V}$.

Once portfolios' returns are calculated in each time period t, we also compute the difference between returns in portfolio n and portfolio one. This return difference depicts the effect or impact of having exposure to companies with high values of the sort variable and firms with low values of the same sort variable. This difference in returns can be express mathematically as:

$$\overline{R}_{Diff,t} = \overline{R}_{n,t} - \overline{R}_{1,t} \tag{5}$$

This return difference is the most vital evidence to detect the cross-sectional relation between variable X and expected future returns. The time-series difference in returns between portfolio n and portfolio one is commonly referred to as the difference portfolio. Thus, we then want to test whether the average return of the difference portfolio is statistically distinguishable from zero. A statistically nonzero average return for the difference portfolio is proof that a cross-sectional relation exists between the sort variable X and average future returns.

Finally, the portfolio analysis approach requires to discover whether the pattern in the portfolios' average returns persists after controlling for systematic risk factors. The basic idea behind this step is to run a time-series regression with $\overline{R}_{n,t}$ or $\overline{R}_{Diff,t}$ on the left-hand side and risk factor(s) on the right-hand side. There are three most known and accepted factor models used in the finance literature: the CAPM One-Factor Model, Fama-French Three-Factor Model, and Carhart Four-Factor Model. The CAPM One-Factor Model, developed by Sharpe (1964), Lintner (1965), and Mossin (1966), describes the relationship between systematic risk represented by β and the expected return of a market and the risk-free asset.

For any risky asset, efficient or not, the following relation must hold:

$$\overline{r}_{n,t} = \alpha + \beta_{MKT} MKT_t + \varepsilon_t \tag{6}$$

Where $\overline{r}_{n,t}$ and MKT_t are the excess return over the risk-free rate, R_f, of the portfolio n and the market factor mimicking portfolio in time period t, respectively.

The second risk factor model, proposed by Fama and Frech (1993), comes up with the idea that a size and a book-to-market effect do a good job explaining the cross-section of average returns on stocks. The size effect alludes to the fact that small-cap companies outperform on average large-cap companies in the long run. Therefore, this effect can be accomplished by creating a zero-cost portfolio that goes long small-cap stocks and goes short large-cap stocks simultaneously. Contrarily, the Value effect denotes the fact that firms with high book-to-market ratios (Value stocks) outperform on average firms with low book-to-market ratios (growth stocks) in the long run. Consequently, this effect can be realized by creating a zero-cost portfolio that goes long Value stocks and goes short growth stocks simultaneously. Thus, the Fama-French three-factor model is:

$$\overline{r}_{n,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \varepsilon_t \tag{7}$$

Where SMB_t and HML_t are the returns of the Size and Value zero-cost (mimicking) portfolios in time period t, respectively.

The third most used risk factor model extends the Fama-French three-factor model with the Momentum anomaly documented by Jegadeesh and Titman (1993) and then formalized by Carhart (1997). The Momentum factor represents the return of a zero-cost portfolio that goes long stocks with the highest recent past performance based on the cumulative returns of the past 12 to 1 months and goes short stocks with the lowest recent past performance based on the same cumulative returns. The risk factor model that includes the Momentum effect is known as the Carhart four-factor model and can be written as:

$$\overline{r}_{n,t} = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \varepsilon_t \tag{8}$$

Where MOM_t represents the returns of the Momentum zero-cost (mimicking) portfolio in time period t. Having performed the regressions, we obtain the values for the intercept, α, and slopes, βs, as well as their $t - statistics$ and $p - values$. The intercept coefficient, α, is known as the average abnormal return of the corresponding portfolio, P_n, that is not related to the sensitivity of any of the risk factors included in the model employed. Therefore, testing whether the average abnormal return is statistically distinguishable from zero and positive is a piece of evidence that forming portfolios based on the variable X may have recourse to earn future positive excess returns not explained by common risk factors. Besides, the coefficients to the risk factors can be used to adjudge which factors better explain the returns of the underlying portfolio.

5.2 Bivariate independent-sort analysis

Most research papers in asset pricing use the equity factors developed by Fama and Frech (1993) available to be downloaded from the website of Kenneth French. The factors ($RM - Rf$, SMB, HML, and MOM) are constructed by using all NYSE, AMEX, and NASDAQ firms. The Fama/French factors are set up to show evidence of the relation between size, book-to-market, and Momentum with asset returns in the US equity market. However, we believe it is not convenient to utilize them as they are not represented within our sample data (i.e., LatAm equities). Thus, using LatAm equity returns only we construct SMB, HML, and MOM to control portfolio returns by using the "appropriate" systematic risk factors according to equations (6), (7) and (8).

Small minus Big (SMB) is the difference between the equally-weighted return of three portfolios containing small-caps and three portfolios containing large-caps as follows[6]:

$$\begin{aligned} SMB =& (\text{Small Value} + \text{Small Neutral} + \text{Small Growth})/3 \\ & - (\text{Big Value} + \text{Big Neutral} + \text{Big Growth})/3 \end{aligned} \tag{9}$$

High minus Low (HML) is the difference between the equally-weighted return of two portfolios containing Value firms and two portfolios containing Growth firms. Then, we have[6]:

$$\begin{aligned} HML =& (\text{Small Value} + \text{Big Value})/2 \\ & - (\text{Small Growth} + \text{Big Growth})/2 \end{aligned} \tag{10}$$

Finally, the Momentum factor (MOM) is constructed by taking the difference between the equally-weighted return of two portfolios containing high past cumulative returns and low past cumulative returns as follows[6]:

$$\begin{aligned} MOM =& (\text{Small High} + \text{Big High})/2 \\ & - (\text{Small Low} + \text{Big Low})/2 \end{aligned} \tag{11}$$

[6] This formula is taken exactly as it appears on Kenneth French's website.

It must be noted that the approach to factor creation is consistent with a bivariate independent-sort analysis. This methodology is very similar to the one described in section 5.1 except that there are, in this particular case, two sort variables X. Thus, portfolios are created by sorting stocks on two variables independently. In each period t, two sets of breakpoints will be computed based on values of variable X_1 and X_2. As in the portfolios analysis approach, the first step in the bivariate independent-sort analysis is to classify companies into sets according to the two sort variables. Thus, the portfolios will represent intersections of firms based on variable X_1 and X_2 as in equations (9), (10), and (11).

Consequently, we will have n_{p1} portfolios formed based on variable X_1 and n_{p2} portfolios formed based on variable X_2. The total number of formed portfolios is therefore equivalent to n_{p1}*n_{p2}. The breakpoints for variable X_1 and X_2 will be calculated in the same manner as for a univariate portfolio analysis and each portfolio will be conformed of firms conditional to having exposure independently to variable X_1 and X_2 as follows:

$$P_{n,k,t} = \{i|B1_{n,t-1} \leq X_{i,t} \leq B1_{n,t}\} \cap \{i|B2_{k,t-1} \leq X_{i,t} \leq B2_{k,t}\} \tag{12}$$

Where the first part corresponds to firms of the first sort variable, X_1, and the second part corresponds to firms of the second sort variable, X_2. The next step is to compute the average return for each portfolio and the difference portfolios by using the same approach described by equation (4) and (5).

We follow the approach developed by Fama and French to create risk factors. Hence, in June of each year t from 1999 to 2018 all LatAm stocks from Compustat Global and Bloomberg are ranked according to size (i.e., market cap) and stocks are split into two groups (small-caps and large-caps). We also use the book-to-market-equity ratio to split stocks into three groups (Value, Neutral, and Growth firms). The book-to-market equity ratio is computed by taking the book common equity from the balance sheet of company i for the fiscal year $t-1$, divided by the market capitalization of company i by the end of the fiscal year $t-1$. Therefore, we use the bivariate independent-sort analysis to create six portfolios from the intersection of the two portfolios formed based on size, and the three portfolios formed based on book-to-market-equity ratio. We then follow equation (9) and (10) to create SMB and HML by computing monthly value-weighted returns from July of year t to June of year $t+1$. All portfolios' constituents are upgraded on June of year $t+1$. Finally, we create the Momentum mimicking portfolio (MOM) by employing six value-weighted portfolios formed by the intersection of two portfolios ranked according to size and three portfolios ranked according to the cumulative returns of the past 12 to 2 months.

5.3 Defining factors in the equity market

The following section describes how we create portfolios and how we evaluate them. We mainly follow the approaches that were established by previous researchers.

5.3.1 Momentum

Following the approach of Jegadeesh and Titman (1993), every month we sort stocks into 10 decile portfolios, by whole sample breaks, based on the cumulative returns of the past 12 to 1 months (inclusive) prior to portfolio formation ($MOM_{12,1}$). Further, we calculate the equally-weighted returns for each decile portfolio across all months. To construct the Momentum strategy, we take the difference in monthly returns between the top and the bottom decile (which is the equivalent to going long in the top decile portfolio while shorting the bottom decile portfolio). Additionally, we also incorporate the methodology of Novy-Marx (2012), who find that intermediate past performance primarily drives Momentum. Thus, we use two cumulative returns, namely the past 12 to 7 months (inclusive) ($MOM_{12,7}$) and the past 6 to 2 months (inclusive) ($MOM_{6,2}$), to create 10 decile portfolios. Mathematically, the Momentum of stock i in period t can be expressed as follows:

$$MoM_{i,t} = \left[\prod_{m \in [t-j:t-k]} (1 + R_{i,m}) \right] - 1 \tag{13}$$

Where $[t-j : t-k]$ represents the period in which the cumulative return must be computed, being $t-j$ the oldest date and $t-k$ the earliest date. Finally, in order to assess the explanatory power of different factor exposures, such as Size or Value, each decile portfolio is regressed against the CAPM, Fama, and French three-factor model and Carhart four-factor model accordingly to equations (6), (7) and (8), respectively.

In their seminal paper, a model of investor sentiment, Barberis, Schleifer, and Vishny (1999) introduce a first model to explain underreaction of stock prices to new information and overreaction of stock prices to both good and bad news. This model supports the recent findings reported by Jegadeesh and Titman (1993) who argue that Momentum is mainly caused by underreaction to positive news by market participants. In 2014, Da, Gurun, and Warachka (2014) documented further evidence of the underreaction of stock prices by market participants. In this paper, the authors tested what they called the frog-in-the-pan hypothesis, which states that investors suffer from "limited attention" and are distracted to new information coming out in small amounts. In other words, they test that gradual changes in stock prices draw less attention than unusual and rare changes. For instance, if a stock price changes by 50% a month, then this change will attract the attention of investors immediately than if the price change occurs during twelve months. Therefore, they find that continuous information in securities' returns creates a persistent return continuation than discrete information in securities' returns does.

To measure information discreteness (ID), Da, Gurun, and Warachka (2014) create an ID sign that measures the relative frequency of small signals in a particular formation-period return. Thus, the ID measure is determined by the sign (i.e., positive or negative) of the daily returns in the formation period. As a result, if a past winner's formation-period Momentum is mainly driven by a high percentage of positive changes relative to negative changes, then the flow of information is continuous. In contrast, if the percentage of positive changes is small relative to negative changes, then the flow of information is discrete. In other words, the path dependency of Momentum is important. In this research, we refer to continuous information as to Quality Momentum. Consequently, we leverage our understanding of Quality Momentum from Da, Gurun, and Warachka (2014) to create a sign that helps to determine the Quality of the path dependency in Momentum returns. The idea behind this strategy is to select firms with positive Momentum whose stocks price's changes have presented continuous information over the formation period and avoid firms with negative Momentum and continuous information as well. We test the Quality Momentum strategy using the generic $r_{12,1}$ formation period. We create our Quality Momentum sign as follows:

$$\text{QM Sign}_{i,t} = \begin{cases} MoM_{12,1i,t} * \frac{\#\text{ Positive monthly } returns_{12,1}}{\#\text{ Negative monthly } returns_{12,1}}, & \text{if } MoM_{12,1i,t} \geq 0 \\ MoM_{12,1i,t} * \frac{\#\text{ Negative monthly } returns_{12,1}}{\#\text{ Positive monthly } returns_{12,1}}, & \text{Otherwise} \end{cases} \tag{14}$$

We then sort stocks into decile portfolios according to the definition of Eq (14). Thus, top decile portfolios would contain stocks with positive Momentum and continuous information; whereas bottom decile portfolios would contain stocks with negative Momentum and continuous information. The decile portfolios in between would contain stocks with positive and negative Momentum with discrete information. Therefore, for this particular strategy, decile portfolios D1 and D10 are of the most interest.

5.3.2 Value

Taking into consideration the research paper by Fama and Frech (1993), we create ten decile portfolios based on the book-to-market ratio[7] monthly. Thus, D10 contains stocks with the highest book-to-market ratio (cheap stocks), while D1 contains stocks with the lowest book-to-market ratio (expensive stocks). Also, every month, we calculate the equally-weighted returns for each decile portfolio. To determine evidence of the value effect, we also compute the return for the difference portfolio (D10-1). It is worth mentioning here that in order to avoid look-ahead bias, all stocks are sorted using a six-month lag in the companies' common equity book value. For instance, the sorting of stocks in every July of year t is done using December of year $t-1$ balance sheet data, but employing contemporaneous market value data. As companies have different reporting dates, we assume all accounting data will be available to investors with a six-month lag. Therefore, the following calculation holds for the book-to-market ratio in period t:

$$\text{Book-to-market ratio}_{i,t} = \frac{\text{Common equity book value}_{i,t-6}}{\text{Equity market value}_{i,t}} \tag{15}$$

The portfolios' returns are regressed against the CAPM, Fama and French three-factor model and Carhart four-factor model according to equations (6), (7) and (8), respectively.

Additionally, we use three different price ratios to assess the attractiveness of this strategy with distinct Value definitions. Therefore, we use the Net Income-to-Market Equity ratio, the EBIT-to-Enterprise Value ratio, and the Operating Profit-to-Enterprise Value ratio. This comparison will allow determining which price ratio is the strongest when creating excess returns in LatAm equity markets. The Net Income-to-Market Equity ratio is simply the inverse of the well-known Price-to-Earnings ratio. We calculate this ratio as follows:

$$\text{Net Income-to-Market Equity ratio}_{i,t} = \frac{\text{Net income}_{i,t-6}}{\text{Equity market value}_{i,t}} \tag{16}$$

For the next two price ratios, we use in the denominator the Enterprise Value of a firm instead of the Market Equity. This measure is a good proxy of the market value of a company as it reflects an acquirer's true cost of acquisition. This measure takes into account all the liabilities the acquirer would assume if it wants to take over the company as a whole, all the equity represented as both common and preferred shares minus the cash and investments the

[7] The book-to-market ratio is calculated as the value of a company's common equity to the equity market value. The book value figure is found in any company's balance sheet, while the market value is calculated as the number of shares outstanding times the firm's current market price.

company holds into its bank accounts and portfolios. Consequently, the Enterprise Value can be described as:

$$\begin{aligned}\text{Enterprise Value}_{i,t} = &\text{ Market value of common shares}_{i,t-6} + \text{total debt}_{i,t-6} \\ &- \text{Cash and investments}_{i,t-6} + \text{Preferred shares}_{i,t-6}\end{aligned} \tag{17}$$

We also use Earnings before Interests and Taxes (EBIT) and Operating Profit to reflect companies' ability to generate cash with its core activities. This could be thought as the cash flowing into the acquirer's balance sheet upon acquisition. We calculate the EBIT-to-Enterprise Value as follows:

$$\text{EBIT-to-Enterprise Value ratio}_{i,t} = \frac{\text{EBIT}_{i,t-6}}{\text{Enterprise Value}_{i,t-6}} \tag{18}$$

It is important to mention here that the EBIT calculation is not available for banks and insurers. Therefore, this price ratio will allow determining the Value anomaly in LatAm equity markets ex Financials. Finally, we calculate the Operating Profit-to-Enterprise Value following the same logic and procedure as in previous definitions. Therefore,

$$\text{Operating Profit-to-Enterprise Value ratio}_{i,t} = \frac{\text{Operating Profit}_{i,t-6}}{\text{Enterprise Value}_{i,t-6}} \tag{19}$$

5.3.3 Low Volatility

In light of the research paper by Blitz and van Vliet (2007), we form 10 decile portfolios based on 3-year volatility using the standard deviation of returns. Therefore, D1 portfolio contains stocks with the lowest volatility among the sample for every month, and D10 portfolio holds the highest volatility stocks. Contrary to the other strategies, we calculate the return of the strategy as D1-D10 instead of D10-D1. These portfolios are rebalanced monthly. Despite Blitz and van Vliet (2007) examine only large-cap companies, we use the whole sample to determine whether the anomaly holds among small and large-cap stocks alike. Therefore, the volatility of each stock i in period t is computed using a simple standard deviation calculation:

$$Vol_{i,t} = \sqrt{\frac{\sum_{tn=1}^{n}(R_{i,t} - \overline{R}_i)^2}{n-1}} \tag{20}$$

As mentioned before, the portfolio returns are regressed against the CAPM, Fama-French three-factor model and Carhart four-factor model according to equations (6), (7) and (8), respectively.

5.3.4 Quality

Following Asness, Frazzini, and Perdersen (2013), we use the definition of Quality to form 10 decile portfolios based on three criteria: $profitability$, $growth$, and $safety$. Then, the Quality minus Junk approach is tested by buying the highest Quality decile and selling the lowest Quality (i.e., Junk) decile. If a company does not have a Z-score for all components, then the company is excluded from the analysis for that month. Asness, Frazzini, and Perdersen (2013) split the Quality factor into three categories. They define $profitability$ as:

$$Profitability = z(z_{gpoa} + z_{roe} + z_{roa} + z_{cfoa} + z_{gmar} + z_{acc}) \tag{21}$$

The $profitability$ score takes into account the gross profit over assets (GPOA), return on equity (ROE), return over assets (ROA), cashflow over assets (CFOA), gross margin (GMAR) and the fraction of earnings composed of cash (i.e level of accruals). Standardizing them using their respective Z-score and converting them into ranks every month allows us to maintain steady measurement of those factors. The Z-score is measured as:

$$Z(x) = \frac{R(x) - \mu(R)}{\sigma(R)} \tag{22}$$

Similarly, they measure $growth$ as the five-year prior growth in $profitability$ measures, and then average across these measures of $growth$:

$$Growth = z(z_{\delta gpoa} + z_{\delta roe} + z_{\delta roa} + z_{\delta cfoa} + z_{\delta gmar} + z_{\delta acc}) \tag{23}$$

where δ denotes the five-year growth rate computed as:

$$\delta_i = \frac{X_{i,t} - X_{i,t-5}}{X_{i,t-5}} \tag{24}$$

The last Quality factor, $safety$, is composed of low beta (BAB) (Frazzini and Pedersen (2013)), low idiosyncratic volatility (IVOL), low leverage (LEV), low bankruptcy risk (Ohlson's o-score and Altman's Z score) and low ROE volatility (EVOL):

$$Safety = z(z_{bab} + z_{ivol} + z_{lev} + z_{o} + z_{zed} + z_{evol}) \tag{25}$$

Finally, we take the average of the three risk factors to obtain our $Quality$ score.

$$Quality = z(Profitability + Growth + Safety) \tag{26}$$

Again, the CAPM, Fama-French three-factor model and Carhart four-factor model are used to show the explanatory power of factor exposures on Quality portfolios according to equations (6), (7) and (8), respectively.

5.4 Constructing multi-factor portfolios

5.4.1 The portfolio and the signal blending approach

Current existing literature has shown that single-factor strategies described in Section 5.3 may experience periods of underperformance that can last many months or even years. It may cause impatient investors to start blaming asset managers for the poor results. Consequently, as factors tend to have low correlations among them, a new wave of research has emerged as to find the best way of combining single factors and take advantage of the potential diversification benefits when uniting single strategies. The two most commonly used methodologies to multi-factor portfolio construction are the portfolio and the signal blending approach. The portfolio mix approach is usually a two-step process. In the first step, single-factor portfolios are formed using the methodology described in Section 5.1. That is, decile portfolios are constructed according to the desired underlying characteristics explained in Section 5.3. In the second step, the single-factor portfolios are merged to create multi-factor portfolios by using two or more strategies simultaneously. The weights to each strategy are set equally. We create seven multi-factor portfolios: six multi-factor portfolios by using pairs combinations of Value, Momentum, Low Volatility, and Quality; and one multi-factor portfolio that invests equally in all strategies. Thus, the portfolio approach to multi-factor strategies can be described as follows:

$$\begin{aligned} Portfolio_{Approach_t} =& (\frac{1}{n}) * Factor_{1_t} + (\frac{1}{n}) * Factor_{2_t} \\ & + ... + (\frac{1}{n}) * Factor_{n_t} \end{aligned} \tag{27}$$

where n is the number of factor portfolios to be used to create a diversified multi-factor strategy. On the other hand, in the signal blending approach, individual factor scores are combined to create an overall composite score. For instance, the Low Volatility signal and the Quality signal are put together into Low Volatility plus Quality composite signal. Then, stocks are sorted on decile portfolios according to the composite signal. Thus, to combine multiple factors, the methodology introduced by Asness, Frazzini, and Perdersen (2013) to merge various strategies is employed. Therefore, each strategy's characteristic is standardized by using the Z-score formula introduced in Section 5.3.4 and, then, an average Z-score is computed to get an overall composite signal. Finally, decile portfolios are constructed, and long-only multi-factor portfolios will be considered among the most profitable strategies.

5.4.2 Testing single- vs multi-factor portfolios through GRS test

We use the methodology developed by Gibbons, Ross, and Shanken (1989) to determine whether multi-factor strategies are superior compared to single-factor strategies. Usually, the GRS test is used to determine the explanatory power of an asset pricing model. However, Gibbons, Ross, and Shanken (1989) also show how the GRS test is associated with Sharpe ratios. A rejection of the null hypothesis for this test does not only mean that test assets can generate alphas that are statistically different from zero but that by combining these assets with the factors implied for any particular asset pricing model, an improvement in Sharpe ratios can be generated. Therefore, from a statistical point of view, the higher the GRS statistic, the greater the chance to reject the null hypothesis and, thus, the more pronounced the enhancement in Sharpe ratios when using any particular set of test assets. As a result, if we compared the GRS statistic resulted from applying the methodology to single-factor portfolios to those reported when multi-factor portfolios are used, then we can statistically demonstrate whether a multi-factor strategy setting delivers better results than a single-factor strategy setting.

From Treynor (1961, 1962), Sharpe (1964), Lintner (1965), and Mossin (1966) we learned that the expected return for any risky asset is derived by the relationship between systematic risk represented by the β and the expected return of the market portfolio and the risk-free asset. Therefore, for any risky asset, efficient or not, the following relation must hold:

$$E(R_i) = R_f + \beta_i(E(R_m) - R_f) + \varepsilon_t \tag{28}$$

Eq (6) was previously referred to as the CAPM model. However, as the CAPM is an economic model, we need an econometric model to determine its validity. Therefore, Eq (6) can also be rewritten as:

$$E(R_i) - R_f = \beta_i(E(R_m) - R_f) + U_i - \beta U_i \tag{29}$$

By calling r as as the expected excess return and α as the error term, we can rewrite Eq (29) as:

$$r_i = \alpha_i + \beta_i \mathrm{r}_m + \epsilon_i \tag{30}$$

Now, Eq (31) is an econometric model that can be empirically tested, and from it, we can expand the number of factors as follows:

$$r_{i,t} = \alpha_i + \beta_i' f_t + \epsilon_i \tag{31}$$

Where $r_{i,t}$ is the excess return on asset i, α_i is the intercept, f_t the vector of factor realizations, β_i' the vector of coefficients for the factors and ϵ_i an error term that has expectation zero. As any asset pricing model asserts that an asset's expected return is determined by its systematic risks times the risk premiums, α_i should be equal to zero. The GRS-Test helps to determine whether an asset pricing model holds. This test assesses whether the intercepts in a set of linear time series regressions are jointly equal to zero. Since GRS-Test is based on classical regression theory for finite samples, we must work under the assumption that errors are independently and identically normally distributed. Thus,

$$\hat{a} \sim N(\alpha_i, q_{11}\sigma_i^2) \tag{32}$$

We need to regress any portfolio's excess return to factor's risk premiums to find α_i and β_i'. This enables to set the hypothesis as follows:

$$\begin{aligned} H_0 &: \alpha_i = 0 \text{ for } i\text{: } 1, 2, 3,..., n \\ H_1 &: \alpha_i \neq 0 \text{ for } i\text{: } 1, 2, 3,..., n \end{aligned} \tag{33}$$

Where n is the number of test assets or portfolios. Therefore, according to Gibbons, Ross, and Shanken (1989), each portfolio's t-statistics can be calculated as:

$$t_i = \frac{\hat{a}_i}{\sqrt{q_{11}\hat{\sigma}_i^2}} \sim t_{T-2} \tag{34}$$

Where q_{11} is the element $(1, 1)$ of Q and $Q = (X'X)^{-1}$. However, as many more portfolios are being tested, Eq (34) is not a relevant proof, since we have to test whether the three factor models hold for the whole market, which will combine all available portfolios. Hence, the GRS-Test is applied with an F-distribution by calculating the F-statistic as follows:

$$Z_i = \frac{T-n-1}{n(T-2)} \frac{1}{q_{11}} \hat{a}' \hat{\Sigma}^{-1} \hat{a} \sim F_{n,T-n-1} \tag{35}$$

Gibbons, Ross, and Shanken (1989) also showed that the Z-statistics are related to Sharpe ratios and how the GRS-Test helps to demonstrate the market portfolio can be improved with test assets with the following expressions:

$$Sh[(r_m, r^{'})] = \sqrt{\hat{a}'\tilde{\Sigma}^{-1}\hat{a} - Sh[r_m]^2} \tag{36}$$

Where $Sh[(r_m, r^{'})]$ is the Sharpe ratio of the efficient portfolio between the market portfolio and the test assets. Therefore,

$$Z_i = \frac{T-n-1}{n(T-2)}\left(1 + \frac{\hat{E}(r_m)^2}{\tilde{Var}[r_m]}\right)^{-1}\hat{a}'\hat{\Sigma}^{-1}\hat{a} \tag{37}$$

5.5 A dynamic asset allocation approach

Along with the empirical evidence of a cross-sectional Momentum anomaly by Jegadeesh and Titman (1993), Moskowitz, Ooi, and Pedersen (2012) developed further the idea behind this effect to discover a new anomaly that they term "time-series Momentum". They are the first to document empirical evidence of a time series Momentum across futures markets in equity indexes, currencies, commodities, and sovereign bonds. They find that the twelve months of past returns are a positive predictor of future returns in these markets by focusing on a security's past data. Relative Momentum seeks to invest in the best performers over a look-back period by buying stocks that have outperformed; while going short or avoiding stocks that have underperformed. Contrarily, time-series Momentum seeks to have exposure to a particular asset class based on its past performance. Therefore, relative Momentum strategies do not care about the Absolute Momentum of an asset class since short positions support long positions. Thus, if the Absolute Momentum is negative, then short positions should outperform long positions and vice-versa. However, as short positions are challenging to hold, many practitioners have focused on long-only relative Momentum strategies which have been proved to be regime dependent. Hence, when implementing Momentum strategies, it is desirable to be long-only when both relative and Absolute Momentum are positive simultaneously.

Based on this evidence, Antonacci (2012) introduces a dual Momentum strategy. He first selects non-Treasury assets based on relative Momentum. However, if the selected Benchmark does not show positive Absolute Momentum concerning Treasury bills, then he invests entirely in Treasury bills until the selected Benchmark Absolute Momentum surpasses the performance of Treasury bills. By implementing the dual Momentum strategy, Antonacci (2012) documents an increase of 4% in excess returns with a reduction of drawdowns in half. He also reports material improvements in Sharpe ratios in credit and real estate portfolios. Therefore, dual Momentum is not a strategy that is uniquely effective in equities.

Consequently, we leverage our understanding of dual Momentum to create a dynamic asset allocation strategy based on Absolute Momentum by using the past performance of the selected Benchmark in this research to decide whether to invest in long-only multi-factor portfolios or in an alternative fixed income portfolio. Thus, every month t from January 2000 to December 2018, we calculate the past twelve months excess returns on the MSCI Emerging Markets Latin America Index as our allocation signal. If the Absolute Momentum of the Index is positive, then we invest in multi-factor portfolios; otherwise, we invest in the Barclays US Aggregate Bond Index [8]. We hold this portfolio until the Absolute Momentum of the Benchmark turns positive again. The idea of the strategy is to benefit from the uptrend in LatAm equity markets; while being defensive in risk-off scenarios and bear markets.

6 Empirical Results

6.1 Constructing systematic risk factors

In order to investigate the influence of firm characteristics on asset prices, we follow a rank portfolio approach by sorting each month the whole-sample of companies in the LatAm region into eighteen different portfolios according to characteristics. Particularly, we follow Fama and Frech (1993)'s approach to risk factor construction. First, we employ the approach described in section 5.2 by independently sorting stocks into size groups and subsequently into market-β, book-to-market equity, and Momentum. This methodology guarantees for variation in these market characteristics that are not related to size. We then use the method described in Eq (9), Eq (10), and Eq (11) to construct risk factors by taking long and short positions in portfolios formed on these characteristics. Table III illustrates the descriptive statistics for eighteen portfolios formed on size-market-β, size-book-to-market equity, and size-Momentum. Table IV shows the descriptive statistics for four systematic risk factors using the whole-sample in LatAm equity markets ranging from January 2000 to December 2018.

The idea behind forming size-market-β portfolios is to add empirical evidence to the existing literature showing that there exists a strong negative relationship between size and returns (Banz (1981)) in the LatAm equity universe, and a negative or neutral relation between returns and market-β. We do not pretend to create a beta risk factor, as this is already represented by our RMRF factor shown in Table IV.

[8] The Barclays US Aggregate Bond Index is a broad bond index made of approximately 17,000 investment-grade fixed-income securities in the USA with an average maturity of five years.

Table III

Descriptive Statistics for the Beta, Size, Value and Momentum Effect

This table gives the monthly descriptive statistics for 18 portfolios formed on beta, size, book-to-market equity, and Momentum from January 2000 to December 2018. The 6 Size-Beta stocks portfolios are created as follows: Each year t from 2000 to 2018, stocks are split into two groups based on the whole-sample market capitalization breakpoints for each month. Similarly, stocks are split into three groups using whole-sample beta breakpoints for each month. The six Size-Beta portfolios are formed based on the intersection of the two sizes and the three beta groups. Additionally, the 6 Size-BE/ME stocks portfolios are created as follows: Each year t from 2000 to 2018, stocks are split into two groups based on the whole-sample market capitalization breakpoints at the end of June of each year t. Similarly, stocks are split into three groups using whole-sample BE/ME breakpoints at the end of year t_{-1}. The 6 Size-BE/ME portfolios are formed based on the intersection of the two sizes and the three BE/ME groups. Finally, the Size-Momentum stocks portfolios are created as follows: Each year t from 2000 to 2018, stocks are split into two groups based on the whole-sample market capitalization breakpoints for each month. Stocks are split into three groups using the whole-sample 12-2 accumulated return breakpoints for each month. The 6 Size-Momentum portfolios are formed based on the intersection of the two sizes and the three 12-2 accumulated return groups.

Panel A: Beta-Sorted Portfolios

	Average Returns			T-Stat for Mean = 0			Standard Errors			P-Values		
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Small	**1.06%*** **	**0.75%** **	0.43%	3.59	1.93	0.71	0.29%	0.39%	0.61%	0.00	0.05	0.48
Big	-0.11%	0.08%	0.34%	-0.18	0.19	0.56	0.63%	0.42%	0.61%	0.86	0.85	0.58

Panel B: Book-to-Market Equity-Sorted Portfolios

	Average Returns			T-Stat for Mean = 0			Standard Errors			P-Values		
	Growth	Neutral	Value	Growth	Neutral	Value	Growth	Neutral	Value	Growth	Neutral	Value
Small	0.58%	**0.92%*** **	**0.77%** **	1.43	2.46	1.81	0.40%	0.37%	0.43%	0.15	0.01	0.07
Big	0.03%	0.33%	0.39%	0.06	0.66	0.65	0.56%	0.50%	0.59%	0.95	0.51	0.52

Panel C: Momentum-Sorted Portfolios

	Average Returns			T-Stat for Mean = 0			Standard Errors			P-Values		
	Down	Medium	Up	Down	Medium	Up	Down	Medium	Up	Down	Medium	Up
Small	0.31%	**1.11%*** **	**0.96%*** **	0.61	3.01	2.51	0.51%	0.37%	0.38%	0.55	0.00	0.01
Big	-0.27%	0.06%	0.49%	-0.47	0.13	0.76	0.56%	0.47%	0.65%	0.64	0.90	0.45

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Panel A of Table III shows that stocks of small firms experience a higher expected return compared to stocks of big firms. However, the relation is inverse when considering systematic risk: high-beta stocks earn, on average, lower expected returns compared to low-beta stocks. These results are consistent with Haugen and Heins (1972) and Basu (1977) who found evidence of a low-beta effect in the US equity market. Panel A of Table III shows that average returns fall from 1.06% per month for the smallest market capitalization portfolio with low-beta stocks to 0.34% per month for the biggest market capitalization with high-beta stocks. Furthermore, average returns are statistically significant for the small-cap low-beta portfolios but are not for the high-beta portfolios. Thus, this is inconsistent for the Sharpe-Lintner-Black model's main prediction: expected returns are positively related to market-β. However, it is essential to mention that the low-beta effect is stronger among small-caps in LatAm equities. For large-caps, the expected output holds.

Panel B of Table III illustrates the two-dimensional relation between average returns that results when individual stocks are subdivided independently based on market capitalization and book-to-market equity. Within each size group, the expected returns increase in sync with rises in BE/ME. On average, for the smallest companies in the sample, the difference in expected returns between Value and Growth firms is 0.19% (0.77% - 0.58%)) per month or 2.28% per year; while for the biggest companies the spread is 0.36% (0.39% - 0.03%)) per month or 4.32% per year. Similarly, looking down the Growth, Neutral, and Value columns, the average returns show that there is a negative relation between size and expected returns. On average, the spread of expected returns across the Value universe is 0.38% per month or 4.56% per year between small and big firms.

Therefore, results from Panel B lead to the conclusion that after controlling for size, book-to-market equity captures average variation in expected returns in LatAm equities; while controlling for book-to-market equity leaves the size effect mostly unchanged. Panel C of Table III shows the descriptive statistics for six size-Momentum portfolios. Overall, average returns increase from the worst performers to the best performers in the six formed portfolios. Compared to the Value effect and the low-beta effect, the Momentum effect is the strongest in the smallest companies in the sample. On average, small companies whose stocks have outperformed similar assets earn 0.65% (0.96% - 0.31%) per month or 7.80% per year more than small companies whose stocks have performed badly recently. Thus, the best performers exhibit positive Momentum returns, but persistence is stronger in the smallest firms. It is worth mentioning here that positive Momentum stocks' standard errors are not as high as those presented by high-beta stocks but are more consistent to Value companies' and in a less extent to low-beta stocks', making its expected average returns statistical significant and different from zero.

Using the performance statistics of portfolios reported in Table III, we construct the SMB (Small Minus Big), HML (High Minus Low), and UMD (Up Minus Down) risk factors to assess the attractiveness of different investment strategies in the LatAm region. Therefore, Table IV summarizes the value-weighted average risk premiums for the risk factors created: the average value for the market premium is 0.85% per month ($t = 1.75$) or 10.20% per year, which is large from an investment point of view and statistically significant. Both, UMD and SMB, are equally large for the sample period. The average UMD return is 0.70% per month ($t = 1.83$) or 8.40% per year; whereas the average value for SMB is 0.52% per month ($t = 2.02$) or 6.24% per year. Meanwhile, HML exhibits a weak performance with an average return of just 0.23% per month ($t = 0.83$) or 2.76% per year. However, as shown in Table III, a Value effect is present in all portfolios studied, and it would be worth including HML as an explanatory variable in the asset pricing models to be employed. High average risk premiums and high volatility among factors will make it easier to explain much of the cross-sectional variation in average returns in LatAm equity markets. Furthermore, a low and negative correlation among factors implies that multicollinearity will not be a problem when estimating each factor loading. Consequently, the CAPM Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model will be used to test different investment strategies in our targeted market.

Table IV
Performance Statistics of VW Systematic Risk Factors

This table gives the monthly descriptive statistics for four systematic risk factors spanning from January 2000 to December 2018 using the whole sample in LatAm equity markets. SMB, HML, and UMD are value-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return using the whole sample of companies in the LatAm region.

Factor Portfolio	Average Returns	Std Deaviation	T-Stat for Mean = 0	P-Value	Pearson Correlations			
					SMB	HML	UMD	RMRF
SMB	**0.52%****	3.86%	2.02	0.04	1.00			
HML	0.23%	4.27%	0.83	0.41	-0.11	1.00		
UMD	**0.70%***	5.80%	1.83	0.07	0.03	-0.45	1.00	
RMRF	**0.85%***	7.31%	1.75	0.08	-0.67	0.06	-0.06	1.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Results reported in Table IV are consistent with risk premiums in other markets. In Section 9.2 of the Appendix, we report the same systematic risk factor for the US from January 2000 to December 2018 [9]. Contrary to LatAm equity markets, all systematic risk factors are particularly weak in the US for the same period. Table XXXVII shows that the average HML and SMB returns are 0.27% per month ($t = 1.28$) and 0.25% per month ($t = 1.16$), respectively. On the other hand, the average risk premiums for UMD and RMRF are 0.21% per month ($t = 0.60$) and 0.38% per month ($t = 1.33$), respectively. Therefore, results in Table III and Table IV support Hypothesis 1 that size, book-to-market equity, and Momentum can explain the cross-section of stock returns in LatAm equity markets. Table V also reports the performance statistics of systematic risk factors but for two different sub-sample periods. Panel A shows the average values of risk premiums from January 2000 to December 2008, and panel B shows the average risk premiums from January 2009 to December 2018. These periods are consistent to the beginning and the end of important business cycles in the global economy as described in Figure 1.

Table V

Subsample Performance Statistics of VW Systematic Risk Factors

This table gives the monthly descriptive statistics for four systematic risk factors spanning from January 2000 to December 2018 using the whole sample in LatAm equity markets. SMB, HML, and UMD are value-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return using the whole sample of companies in the LatAm region.

	Average Returns	Std Deviation	T-Stat for Mean = 0	P-Value	Average Returns	Std Deviation	T-Stat for Mean = 0	P-Value
Panel A: January 2000 to December 2008					**Panel B: January 2009 to December 2018**			
SMB	**0.78%***	4.51%	1.80	0.08	0.28%	3.15%	0.97	0.33
HML	**0.82%****	4.39%	1.94	0.05	-0.29%	4.10%	-0.79	0.43
UMD	**0.99%***	5.93%	1.74	0.08	0.44%	5.69%	0.84	0.40
RMRF	0.69%	8.70%	0.82	0.41	**0.99%***	5.80%	1.88	0.06

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

All factors have experienced periods of excellent and weak performance, mainly in moments of crisis and recessions. For instance, the period from January 2009 to December 2018 was perhaps the most challenging for most systematic risk factors in LatAm. HML had a negative average risk premium of 0.29% per month; while SMB and UMD had weak and not significant performance. Contrarily, the market factor had an outstanding performance of 0.99% per month during this period. This time interval was affected by two crisis in emerging markets: the Financial Crisis in the US and Worldwide (2008) and the recent drop in commodity prices (2014) which affected the performance of most risk factors. From

[9] These factors are taken directly from Kenneth French's website.

January 2000 to December 2018, average risk premiums are more robust, consistent, and stable. The period is characterized by fewer macroeconomic shocks and more companies becoming public, increasing the set of opportunities for investors in the region. All systematic risk factors were overly influential from January 2000 to December 2008. SMB, HML, and UMD reported outstanding and significant average risk premiums of 0.78%, 0.82%, and 0.99% per month, respectively. Despite the average excess return of the Market portfolio is not statistically significant, it is modest at a 0.69% per month. U.S. risk factors performance is also variant and time-dependent. HML and UMD have been dragging in the last ten years as reported by Table XXXVIII. The Market portfolio had a bad performance during the Financial Crisis in the U.S. but recovered significantly after the Quantitative Easing program executed by the Federal Reserve.

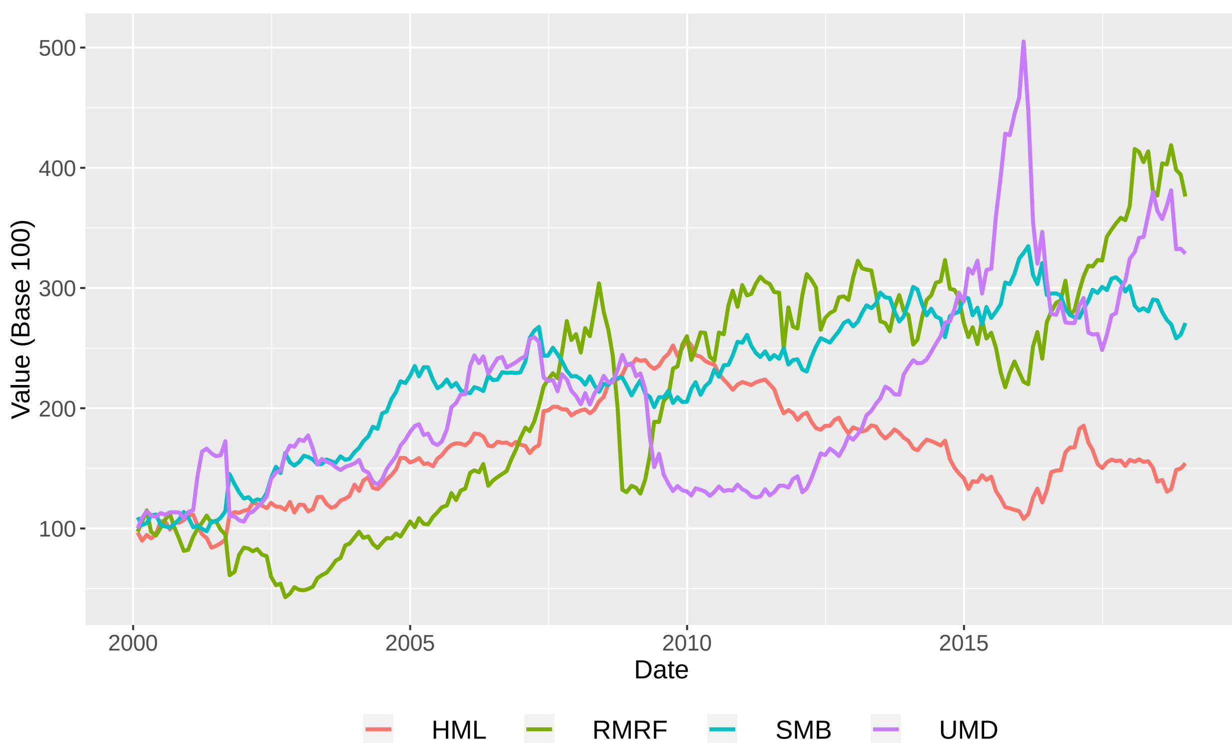

Figure 3
Historical evolution of risk factors. This figure shows the historical evolution of systematic risk factors in LatAm equity markets from January 2000 to December 2018. SMB, HML, and UMD are zero-cost portfolios formed using the methodology described in in Eq (9), Eq (10), and Eq (11).

Figure 3 shows graphically the historical evolution of systematic factors spanning from January 2000 to December 2018. We conclude that different factors (HML and UMD) have experienced periods of lousy performance, mainly in moments of crisis and recessions; while others exhibit a more smoothly behavior (SMB and RMRF). This evidence also opens the debate of combining different strategies to take advantage of low and negative correlations among factors. Surprisingly, our RMRF factor has evolved positively through time even among significant economic shocks in the region; while both UMD and SMB have not been lagging versus the brilliant performance in the Market factor.

6.2 Testing single-factor portfolios

In this section, different investment strategies documented so far in the academic literature will be tested using our sample data. Notably, the Momentum, the Low Volatility, the Value, and the Quality effect will be assessed individually for the last 18 years. We use the portfolio analysis approach described in section 5.1 by creating decile portfolios according to the factors definitions documented in section 5.3. In the first three strategies just mentioned, various variants will be considered to test distinct definitions of the same strategy. The idea behind this approach is not only to test the validity of the empirical evidence documented previously by other authors but also to test how a generic effect could be enhanced. Many statistics will be shown in this section for each strategy, but we will closely watch the average excess returns and their corresponding Sharpe ratios. Apart from the decile portfolios, we also document the performance statistics for the Market factor (i.e., RMRF) and the Benchmark Index, the latter being the MSCI Emerging Markets Latin America Index. The idea is to compare the attractiveness of each strategy not only from an academic point of view (i.e., versus the Market portfolio) but also from a practical perspective (i.e., versus the Benchmark Index). Therefore, we test the statistical significance of the difference between two Sharpe ratios by using the Jobson and Korkie test. Finally, we illustrate the results obtained from the regressions described in Eq (6), Eq (7), and Eq (8) to test the hypothesis of whether the alpha generated by every decile portfolio and, mainly, by the difference portfolio is statistically different from zero. It is also important to mention here that regressions output are reported using White's standard errors and that the average excess returns for each decile portfolio are equally-weighted among the constituents.

6.2.1 Momentum strategies

Table VI shows evidence on what previous literature has reported about the Momentum anomaly. Panel A, B, C, and D indicate that stocks with the highest Momentum (D10) tend to outperform stocks with the lowest Momentum (D1). Excess returns increase from D1 to D10 with decreasing standard deviation. This pattern implies that stocks with the highest Momentum tend to depict a smoother behavior compared to stocks with a lower Momentum, resulting in a higher Sharpe ratio. Even though the Market portfolio presents a higher average return when compared to every decile portfolio for Panel A, B, and C; it does not have a better performance if the winners-minus-losers strategy (D10-1) is considered. It should be noted that results on Panel A, B and C are opposite to Novy-Marx (2012). From 2000 to 2018, the profitability of Momentum is not primarily driven by intermediate past performance in LatAm. Portfolios formed at horizons of 12 to 1 month and at horizons of 6 to 2 months present the best risk-return relationship in Table VI. For example, Panel A illustrates that portfolios formed on one-year past performance experience the highest Sharpe ratio when the winners-minus-losers strategy (D10-1) is implemented using generic Momentum. Furthermore, the top three decile portfolios in Panel A and C hold an average Sharpe ratio of 0.4 and 0.37, respectively compared to an average Sharpe ratio of 0.34 in the top three decile portfolios in Panel B.

Table VI
Descriptive Statistics for Momentum Sorted Portfolios

This table reports the descriptive statistics for forty decile portfolios sorted on $r_{12,1}$, $r_{12,7}$, $r_{6,2}$, and Quality Momentum $r_{12,1}$. LATAM breakpoints are used when sorting on Momentum stocks. D1 contains the stocks with the lowest Momentum, whereas D10 contains stocks with the highest Momentum. D10-1 represents the winners-minus-losers strategy. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio (IR). Beta is the slope of the regression between the returns of each decile portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe ratio of each decile portfolio and the BMK's Sharpe ratio. Data for the risk-free rate are taken from the Kenneth French library. Excess returns are the returns over the 1-month U.S T-Bill. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1	BMK	RMRF
Panel A: Generic Momentum 12,1													
Excess Return	-0.07	0.01	0.04	0.07	0.06	0.06	0.09	0.08	0.09	0.10	0.18	0.03	0.11
Volatility	0.32	0.27	0.24	0.21	0.20	0.19	0.18	0.19	0.21	0.24	0.24	0.27	0.25
Max	0.35	0.26	0.24	0.24	0.17	0.16	0.13	0.12	0.25	0.24	0.17	0.19	0.22
Min	-0.47	-0.41	-0.41	-0.32	-0.36	-0.29	-0.31	-0.27	-0.31	-0.39	-0.29	-0.38	-0.36
Beta	0.98	0.88	0.76	0.68	0.67	0.63	0.60	0.60	0.62	0.73	-0.26	1.00	1.00
Sharpe Ratio	-0.22	0.05	0.16	0.34	0.29	0.33	0.46	0.39	0.41	0.40	0.73	0.10	0.43
T-value	-6.91	-1.49	1.40	5.52	4.60	6.10	8.39	6.19	6.27	6.48	5.72		
IR	-0.52	-0.11	0.08	0.32	0.22	0.25	0.41	0.31	0.36	0.40	0.35		
Panel B: Generic Momentum 12,7													
Excess Return	-0.03	0.00	0.06	0.04	0.06	0.08	0.08	0.07	0.07	0.09	0.12	0.03	0.11
Volatility	0.30	0.26	0.23	0.22	0.20	0.19	0.19	0.19	0.23	0.23	0.22	0.27	0.25
Max	0.29	0.22	0.21	0.20	0.16	0.15	0.17	0.14	0.26	0.26	0.22	0.19	0.22
Min	-0.45	-0.38	-0.39	-0.35	-0.33	-0.34	-0.26	-0.32	-0.35	-0.39	-0.21	-0.38	-0.36
Beta	0.94	0.85	0.76	0.73	0.67	0.62	0.61	0.63	0.68	0.69	-0.24	1.00	1.00
Sharpe Ratio	-0.10	0.00	0.25	0.20	0.31	0.43	0.44	0.33	0.30	0.38	0.57	0.10	0.43
T-value	-4.74	-2.78	3.41	2.83	5.19	7.78	7.62	5.67	4.32	5.72	4.21		
IR	-0.35	-0.20	0.21	0.14	0.27	0.40	0.37	0.28	0.26	0.37	0.23		

Table VI (Continued)
Descriptive Statistics for Momentum Sorted Portfolios

This table reports the descriptive statistics for forty decile portfolios sorted on $r_{12,1}$, $r_{12,7}$, $r_{6,2}$, and Quality Momentum $r_{12,1}$. LATAM breakpoints are used when sorting on Momentum stocks. D1 contains the stocks with the lowest Momentum, whereas D10 contains stocks with the highest Momentum. D10-1 represents the winners-minus-losers strategy. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio (IR). Beta is the slope of the regression between the returns of each decile portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe ratio of each decile portfolio and the BMK's Sharpe ratio. Data for the risk-free rate are taken from the Kenneth French library. Excess returns are the returns over the 1-month U.S T-Bill. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1	BMK	RMRF
Panel C: Generic Momentum 6,2													
Excess Return	-0.05	0.01	0.05	0.05	0.05	0.09	0.07	0.08	0.09	0.08	0.14	0.03	0.11
Volatility	0.33	0.25	0.23	0.22	0.20	0.21	0.20	0.20	0.22	0.23	0.24	0.27	0.25
Max	0.36	0.25	0.24	0.23	0.17	0.23	0.27	0.17	0.22	0.14	0.19	0.19	0.22
Min	-0.50	-0.38	-0.39	-0.35	-0.35	-0.35	-0.29	-0.24	-0.36	-0.37	-0.32	-0.38	-0.36
Beta	0.97	0.80	0.75	0.68	0.65	0.68	0.64	0.65	0.70	0.74	-0.22	1.00	1.00
Sharpe Ratio	-0.17	0.03	0.23	0.21	0.25	0.44	0.37	0.38	0.40	0.34	0.58	0.10	0.43
T-value	-5.62	-1.85	2.79	2.46	3.61	7.93	6.02	7.43	6.35	5.46	4.41		
IR	-0.42	-0.15	0.17	0.13	0.15	0.45	0.31	0.38	0.39	0.35	0.27		
Panel D: Quality Momentum 12,1													
Excess Return	-0.07	0.01	0.04	0.03	0.09	0.06	0.10	0.07	0.09	0.13	0.21	0.03	0.11
Volatility	0.29	0.27	0.25	0.23	0.22	0.19	0.20	0.20	0.20	0.22	0.21	0.27	0.25
Max	0.30	0.29	0.25	0.20	0.26	0.16	0.26	0.12	0.14	0.26	0.19	0.19	0.22
Min	-0.48	-0.41	-0.37	-0.43	-0.29	-0.29	-0.33	-0.31	-0.34	-0.31	-0.25	-0.38	-0.36
Beta	0.91	0.88	0.78	0.74	0.70	0.65	0.67	0.61	0.65	0.66	-0.25	1.00	1.00
Sharpe Ratio	-0.23	0.03	0.16	0.14	0.39	0.33	0.47	0.35	0.42	0.58	0.98	0.10	0.43
T-value	-7.28	-2.04	1.47	0.74	7.05	5.62	8.73	5.37	7.26	9.31	7.62		
IR	-0.55	-0.15	0.10	0.02	0.44	0.27	0.49	0.29	0.40	0.59	0.44		

Surprisingly, RMRF performance is stronger compared to every decile portfolio in Panel A-C. These results are consistent with figures reported previously in Table IV and Figure 3. Therefore, a long-only strategy that uses generic Momentum barely would beat RMRF. However, implementing a (generic) Momentum strategy in LatAM equity markets helps to achieve a higher Sharpe ratio if an investor wants to diversify a passive strategy that only invests in the MSCI Emerging Markets Latin America Index. Finally, Panel D of Table VI (Continued) also documents astonishing results for Quality Momentum. Quality Momentum top decile portfolio (D10) exhibits an average excess return of 13% per year from 2000 to 2018, being the highest performance even among generic Momentum top decile portfolios and the only one that beats the performance of the Market portfolio. Its risk-return trade-off is also promising with a Sharpe ratio of 0.58, the highest in all Momentum decile portfolios considered. Consequently, by directly quantifying the Quality of the path by which stocks are ranked based on generic Momentum, the Momentum anomaly can be significantly enhanced. When implementing a zero-cost strategy by going long the highest-Quality Momentum portfolio while going short the lowest-Quality Momentum portfolio, a stronger Momentum effect can be obtained with a Sharpe ratio that significantly doubles the Sharpe ratio attained by the RMRF factor (0.98 vs 0.43).

Table VII
Regression Outputs for LatAm Decile Momentum Portfolios Based on One-Year Past Performance

This table displays the regression outputs for ten decile portfolios formed based on $r_{12,1}$. D1 contains the stocks with the lowest Momentum, whereas D10 contains the stocks with the highest Momentum. D10-1 represents the winners-minus-losers strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.43*****	**-0.65****	-0.32	0.00	-0.12	-0.04	0.19	0.08	0.16	0.15	**1.58*****
RMRF	**0.98*****	**0.88*****	**0.76*****	**0.68*****	**0.68*****	**0.63*****	**0.60*****	**0.60*****	**0.62*****	**0.73*****	**-0.26*****
Adj-R^2	0.60	0.67	0.63	0.65	0.71	0.74	0.67	0.62	0.57	0.61	0.07
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-2.05*****	**-1.14*****	**-0.82*****	**-0.46****	**-0.54*****	**-0.41****	**-0.31***	**-0.36***	**-0.45***	**-0.54****	**1.50*****
RMRF	**1.18*****	**1.03*****	**0.93*****	**0.84*****	**0.82*****	**0.75*****	**0.78*****	**0.75*****	**0.86*****	**0.99*****	**-0.19****
SMB	**0.61*****	**0.48*****	**0.51*****	**0.48*****	**0.44*****	**0.37*****	**0.55*****	**0.47*****	**0.70*****	**0.77*****	0.16
HML	**0.51*****	**0.41*****	**0.37*****	**0.30*****	**0.29*****	**0.25*****	**0.23*****	**0.30*****	**0.22*****	**0.27*****	**-0.24****
Adj-R^2	0.68	0.74	0.71	0.74	0.79	0.81	0.78	0.72	0.69	0.73	0.09
Panel C: Regression Against Carhart the Four-Factor Model											
Alpha	**-1.53*****	**-0.74*****	**-0.49****	-0.27	**-0.42****	**-0.35****	**-0.37****	**-0.44****	**-0.63*****	**-0.87*****	**0.67***
RMRF	**1.15*****	**1.01*****	**0.90*****	**0.83*****	**0.81*****	**0.75*****	**0.79*****	**0.76*****	**0.87*****	**1.01*****	**-0.14****
SMB	**0.55*****	**0.44*****	**0.47*****	**0.46*****	**0.43*****	**0.37*****	**0.56*****	**0.47*****	**0.72*****	**0.80*****	**0.25****
HML	**0.18****	**0.15****	**0.15****	**0.18*****	**0.21*****	**0.21*****	**0.27*****	**0.35*****	**0.33*****	**0.48*****	**0.30*****
MOM	**-0.52*****	**-0.40*****	**-0.34*****	**-0.20*****	**-0.12*****	**-0.06****	**0.06***	**0.08****	**0.18*****	**0.33*****	**0.85*****
Adj-R^2	0.77	0.81	0.78	0.76	0.80	0.81	0.78	0.72	0.71	0.79	0.49

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Tables VII to X present results of time-series regressions of the four Momentum strategies' returns on the CAPM Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model. Top decile portfolios in the four strategies generate insignificant positive alphas when all factor models are considered. Again, $MOM_{12,1}$ and $MOM_{6,2}$ experience higher alphas when controlled for the market factor compared to $MOM_{12,7}$. However, the Quality $MOM_{12,1}$ depicts better results than the other three generic Momentum strategies. This is fully seen as its top decile portfolio exhibits an alpha of 0.44% per month, but insignificant even at the 10% level. Due to the high average return and volatility reported for the RMRF in Table IV, the Market factor by itself can explain the cross-sectional of average returns of the decile portfolios reported so far. The significant-high betas reported in Panel A of Tables VII to X are an unconditional proof of it. Consequently, alphas from the bottom decile portfolios are significantly negative in the four strategies in line with results reported in Table VI. However, this finding favors the implementation of a strategy that buys the top decile firms while short-sells the bottom decile firms. The alpha for the D10-1 portfolio is close to 1.79% per month, which is significantly different from zero at the 1% level. This finding strongly supports the evidence of a Momentum effect in LatAm equity markets.

Table VIII
Regression Outputs for LatAm Decile Momentum Portfolios Based on Intermediate Past Performance

This table displays the regression outputs for ten decile portfolios formed based on $r_{12,7}$. D1 contains the stocks with the lowest Momentum, whereas D10 contains the stocks with the highest Momentum. D10-1 represents the winners-minus-losers strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.06*****	**-0.73*****	-0.18	-0.25	-0.07	0.14	0.11	-0.01	-0.02	0.11	**1.17*****
RMRF	**0.94*****	**0.86*****	**0.76*****	**0.73*****	**0.67*****	**0.62*****	**0.61*****	**0.64*****	**0.69*****	**0.70*****	**-0.24*****
Adj-R^2	0.63	0.69	0.67	0.72	0.71	0.68	0.69	0.68	0.58	0.58	0.08
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.78*****	**-1.22*****	**-0.77*****	**-0.68*****	**-0.52*****	**-0.35***	-0.29	**-0.47****	**-0.52***	**-0.50***	**1.28*****
RMRF	**1.18*****	**1.01*****	**0.97*****	**0.87*****	**0.83*****	**0.79*****	**0.76*****	**0.80*****	**0.88*****	**0.92*****	**-0.26*****
SMB	**0.75*****	**0.49*****	**0.63*****	**0.43*****	**0.47*****	**0.52*****	**0.43*****	**0.49*****	**0.56*****	**0.67*****	-0.08
HML	**0.51*****	**0.39*****	**0.31*****	**0.34*****	**0.30*****	**0.28*****	**0.24*****	**0.28*****	**0.20*****	**0.30*****	**-0.21****
Adj-R^2	0.74	0.76	0.77	0.80	0.80	0.79	0.77	0.78	0.65	0.68	0.09
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.39*****	**-0.88*****	**-0.53****	**-0.50*****	**-0.40****	-0.28	-0.28	**-0.54*****	**-0.64****	**-0.69*****	**0.70***
RMRF	**1.16*****	**0.99*****	**0.95*****	**0.86*****	**0.82*****	**0.79*****	**0.75*****	**0.80*****	**0.88*****	**0.93*****	**-0.23*****
SMB	**0.70*****	**0.45*****	**0.60*****	**0.41*****	**0.46*****	**0.51*****	**0.42*****	**0.49*****	**0.58*****	**0.69*****	-0.01
HML	**0.26*****	**0.18*****	**0.16*****	**0.23*****	**0.23*****	**0.23*****	**0.24*****	**0.32*****	**0.27*****	**0.43*****	**0.16***
MOM	**-0.39*****	**-0.34*****	**-0.24*****	**-0.18*****	**-0.12*****	**-0.07****	-0.01	**0.06***	**0.12****	**0.20*****	**0.59*****
Adj-R^2	0.79	0.82	0.80	0.82	0.81	0.79	0.77	0.78	0.66	0.70	0.32

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Now, when the CAPM is augmented with the SMB and HML factors, most alphas are further reduced. Panel B of Tables VII to X displays that bottom decile portfolios' alphas become more negative; while top decile portfolios' alphas are lowered close to zero or even become negative in some cases. All Momentum strategies considered garner significant positive loadings on SMB, reinforcing the idea that small companies are what drive the Momentum effect; while the Market factor does not lose its high significance. Furthermore, the HML factor also obtains significant positive loadings but mainly in the bottom decile portfolios, indicating that extreme Momentum firms also exhibit a Value tilt, but mostly in the worst-performers group, as should be natural. This pattern is also consistent with an increase in the value of the Adj-R^2 when factors different from the Market portfolio are used to explain all the Momentum strategies. Interestingly, the alpha generated by the difference portfolio remains intact when Momentum strategies are regressed against the Fama-French Three-Factor Model. This phenomenon is driven by the lack of explanatory power of the model in the bottom decile portfolios. As in the CAPM Model, RMRF garners a significant negative loading on the difference portfolio; while SMB and HML also exhibit negatives or neutral loadings but statistically weak. Once more, neither the SMB factor nor the HML factor can help to explain the performance of a strategy that simultaneously buys and sells Momentum stocks.

Table IX
Regression Outputs for LatAm Decile Momentum Portfolios Based on Recent Past Performance

This table displays the regression outputs for ten decile portfolios formed based on $r_{6,2}$. D1 contains the stocks with the lowest Momentum, whereas D10 contains the stocks with the highest Momentum. D10-1 represents the winners-minus-losers strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.29*****	**-0.63****	-0.23	-0.19	-0.16	0.15	0.04	0.08	0.11	0.01	**1.29*****
RMRF	**0.97*****	**0.81*****	**0.75*****	**0.68*****	**0.66*****	**0.68*****	**0.64*****	**0.66*****	**0.70*****	**0.75*****	**-0.23*****
Adj-R^2	0.57	0.66	0.67	0.60	0.70	0.68	0.65	0.70	0.63	0.65	0.05
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.80*****	**-1.11*****	**-0.66*****	**-0.65****	**-0.6*****	**-0.38****	**-0.43****	**-0.36****	**-0.57****	**-0.67*****	**1.13****
RMRF	**1.12*****	**0.96*****	**0.90*****	**0.84*****	**0.82*****	**0.87*****	**0.81*****	**0.81*****	**0.95*****	**0.99*****	-0.14
SMB	**0.48*****	**0.47*****	**0.45*****	**0.49*****	**0.48*****	**0.58*****	**0.51*****	**0.47*****	**0.75*****	**0.72*****	0.24
HML	**0.50*****	**0.41*****	**0.29*****	**0.29*****	**0.19*****	**0.26*****	**0.24*****	**0.29*****	**0.29*****	**0.38*****	-0.12
Adj-R^2	0.63	0.74	0.73	0.67	0.77	0.78	0.74	0.79	0.76	0.78	0.06
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.34*****	**-0.83*****	**-0.45***	**-0.47***	**-0.45****	**-0.34***	**-0.42****	**-0.44****	**-0.69*****	**-0.81*****	0.53
RMRF	**1.09*****	**0.94*****	**0.89*****	**0.83*****	**0.81*****	**0.87*****	**0.81*****	**0.81*****	**0.96*****	**1.00*****	-0.10
SMB	**0.43*****	**0.44*****	**0.43*****	**0.47*****	**0.46*****	**0.58*****	**0.51*****	**0.47*****	**0.76*****	**0.74*****	**0.31****
HML	**0.21****	**0.23*****	**0.16*****	**0.17*****	**0.10****	**0.24*****	**0.23*****	**0.34*****	**0.37*****	**0.47*****	**0.26****
MOM	**-0.46*****	**-0.29*****	**-0.22*****	**-0.19*****	**-0.15*****	-0.04	-0.01	**0.08****	**0.12*****	**0.14*****	**0.61*****
Adj-R^2	0.69	0.78	0.75	0.69	0.79	0.78	0.74	0.80	0.77	0.79	0.25

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Finally, when the MOM factor is included in the Carhart Four-Factor Model, various elements should be analyzed. As expected, decile portfolios' alphas are closer to zero compared to the alphas generated when the CAPM and the Fama-French Three-Factor Model were used. However, for the first two bottom portfolios, the Carhart Four-Factor Model lacks the explanatory power to account for the cross-sectional average returns in these portfolios as alphas are significantly negative. This causes that the model that incorporates the Momentum factor is still not able to explain the cross-sectional average returns of the D10-1 portfolio. The difference portfolio's alpha is the highest when the Quality Momentum strategy is implemented. The alpha for this strategy is 1.12% monthly or 13.44% per year from

2000 to 2018. Therefore, as mentioned before, quantifying the Quality of the path by which stocks are ranked based on generic Momentum can strengthen the Momentum effect. On the other hand, as predicted, the Momentum factor gathers statistically significant loadings for the long-only top decile portfolios. Now, for the D10-1 portfolio, MOM is the only risk factor that barely explains the average excess returns positively at a high significance level. Consequently, despite we use a factor model that incorporates a Momentum effect, a strategy that buys and sells stocks simultaneously based on past performance is still a puzzle for the Efficient Market Hypotheses (EMH) in LatAm equities.

Table X

Regression Outputs for LatAm Decile Momentum Portfolios Based on Quality One-Year Past Performance

This table displays the regression outputs for ten decile portfolios formed based on Quality $r_{12,1}$. D1 contains the stocks with the lowest Momentum, whereas D10 contains the stocks with the highest Momentum. D10-1 represents the winners-minus-losers strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.35*** **	**-0.70** **	-0.34	-0.39	0.10	-0.06	0.20	0.07	0.13	0.44	**1.79*** **
RMRF	**0.91*** **	**0.89*** **	**0.79*** **	**0.74*** **	**0.71*** **	**0.67*** **	**0.66*** **	**0.61*** **	**0.66*** **	**0.67*** **	**-0.25*** **
Adj-R^2	0.62	0.68	0.65	0.69	0.67	0.73	0.69	0.58	0.66	0.59	0.09
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-2.02*** **	**-1.18*** **	**-0.81*** **	**-0.81*** **	**-0.39* **	**-0.48*** **	-0.26	**-0.44* **	**-0.42** **	-0.24	**1.78*** **
RMRF	**1.14*** **	**1.04*** **	**0.94*** **	**0.88*** **	**0.87*** **	**0.80*** **	**0.83*** **	**0.80*** **	**0.86*** **	**0.91*** **	**-0.23*** **
SMB	**0.70*** **	**0.49*** **	**0.47*** **	**0.43*** **	**0.51*** **	**0.42*** **	**0.50*** **	**0.56*** **	**0.61*** **	**0.74*** **	0.04
HML	**0.43*** **	**0.37*** **	**0.39*** **	**0.34*** **	**0.34*** **	**0.31*** **	**0.24*** **	**0.22*** **	**0.24*** **	**0.32*** **	-0.12
Adj-R^2	0.71	0.74	0.73	0.76	0.76	0.81	0.77	0.67	0.77	0.73	0.09
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.64*** **	**-0.79*** **	**-0.47** **	**-0.59*** **	-0.27	**-0.40** **	-0.26	**-0.55** **	**-0.58*** **	**-0.52** **	**1.12*** **
RMRF	**1.12*** **	**1.02*** **	**0.91*** **	**0.87*** **	**0.86*** **	**0.80*** **	**0.83*** **	**0.81*** **	**0.87*** **	**0.93*** **	**-0.19*** **
SMB	**0.66*** **	**0.44*** **	**0.43*** **	**0.41*** **	**0.49*** **	**0.41*** **	**0.50*** **	**0.57*** **	**0.62*** **	**0.77*** **	0.12
HML	**0.19** **	**0.12** **	**0.17*** **	**0.19*** **	**0.26*** **	**0.26*** **	**0.24*** **	**0.29*** **	**0.34*** **	**0.49*** **	**0.31*** **
MOM	**-0.39*** **	**-0.40*** **	**-0.35*** **	**-0.23*** **	**-0.12*** **	**-0.08** **	0.00	**0.11** **	**0.16*** **	**0.28*** **	**0.67*** **
Adj-R^2	0.76	0.81	0.79	0.80	0.77	0.82	0.77	0.68	0.79	0.78	0.41

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.2.2 Value strategies

Table XI shows the performance statistics of decile portfolios formed on different definitions of Value. We decided to create portfolios using the traditional measure of Value, that is the Book-to-Market Equity ratio, and alternate this definition with income-generating items to see how decile portfolios perform with these metrics. For instance, Panel A of Table XI shows the descriptive statistics of decile portfolios sorted on Book-to-Market Equity; whereas Panel B, C, and D show the performance of decile portfolios sorted on Net Income-to-Market Equity, Operating Profit-to-Enterprise Value, and EBIT-to-Enterprise Value, respectively. On the overall, there is an increasing pattern in the excess return from decile portfolio D1 to decile portfolio D10 in any of the Value metrics. Therefore, our results support the empirical evidence of the existing literature about the presence of a Value effect, but in this case, in LatAm equity markets. From Table XI, it is evident that Value definitions different from the Book-to-Market Equity ratio earn better risk-adjusted returns compared to the RMRF. The top decile portfolio (D10) in Panel C and D earn, on average, an astonishing annual excess return of 16% and 15% and achieve an annual Sharpe ratio of 0.79 and 0.73, respectively. Nevertheless, the performance is more consistent when top decile portfolios are sorted on Net Income-to-Market Equity.

Consequently, if an investor wants to exploit the Value anomaly, it is better to rank stocks based on income-generating items rather than on Book Equity. On the long-term, stocks' prices are more correlated to earnings generation than to book equity. Therefore, defining Value based on income-generating ratios could be a better proxy for valuation. Using Enterprise Value rather than market equity as a measure of the real value of a company delivers better results too. It is worth mentioning that the EBIT-to-Enterprise Value multiple excludes Financials from our data sample as this item is not available for banks and insurers. As a result, Panel D of Table XI documents evidence of a Value anomaly in LatAm equity markets ex-Financials. However, the performance does not vary significantly compared to other metrics that include all companies in the sample.

Additionally, from Panel A to D, all bottom decile portfolios experience negative excess returns. Therefore, growth stocks or companies whose price multiples are relatively low earn, on average, negative risk-adjusted returns. Thus, a strategy that buys cheap stocks and sells-short expensive stocks earns meaningful excess returns. All difference portfolios experience performances that beat the RMRF factor and, more importantly, a passive strategy that invests exclusively on the MSCI Emerging Markets Latin America Index. These results are consistent with Fama and French (1992) who find that companies with high B/M ratios tend to earn higher excess returns compared to companies with low B/M ratios in the United States. We also report the regression outputs after performing Eq (6), Eq (7), and Eq (8) on Value sorted portfolios in Tables XII to XV. Surprisingly, top decile portfolios sorted using Operating Profit and EBIT generate positive alphas that are significant even at the 1% level when the Market portfolio is used to explain the cross-sectional variation in these two strategies.

Table XI
Descriptive Statistics for Value Sorted Portfolios

This table reports the descriptive statistics for forty decile portfolios sorted on Book-to-Market Equity, Net Income-to-Market Equity, Operating Profit-to-Enterprise Value, and EBIT-to-Enterprise Value. LATAM breakpoints are used when sorting on value stocks. D1 contains the most expensive stocks, whereas D10 contains the cheapest stocks. D10-1 represents the cheap-minus-expensive strategy. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio (IR). Beta is the slope of the regression between the returns of each decile portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe ratio of each decile portfolio and the BMK's Sharpe ratio. Data for the risk-free rate are taken from the Kenneth French library. Excess returns are the returns over the 1-month U.S T-Bill. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1	Bmk	RMRF
Panel A: Book-to-Market Equity													
Excess Returns	-0.03	0.04	0.01	0.04	0.03	0.08	0.06	0.08	0.09	0.08	0.12	0.03	0.11
Standard Deviation	0.24	0.19	0.22	0.20	0.21	0.22	0.20	0.21	0.23	0.24	0.16	0.27	0.25
Max	0.24	0.17	0.19	0.20	0.17	0.28	0.17	0.17	0.24	0.20	0.16	0.19	0.22
Min	-0.34	-0.29	-0.40	-0.37	-0.30	-0.38	-0.31	-0.39	-0.33	-0.34	-0.18	-0.38	-0.36
Beta	0.78	0.64	0.76	0.68	0.67	0.70	0.66	0.68	0.74	0.72	-0.06	1.00	1.00
Sharpe Ratio	-0.13	0.20	0.03	0.19	0.13	0.35	0.29	0.37	0.42	0.34	0.76	0.10	0.43
T-Value	-6.03	2.60	-2.07	2.23	0.65	5.73	4.62	6.47	7.44	4.87	6.31		
IR	-0.44	0.08	-0.16	0.08	-0.01	0.34	0.23	0.36	0.47	0.34	0.27		
Panel B: Net Income-to-Market Equity													
Excess Returns	-0.04	0.02	-0.01	0.01	0.03	0.06	0.05	0.10	0.14	0.11	0.16	0.03	0.11
Standard Deviation	0.27	0.23	0.22	0.21	0.21	0.19	0.21	0.20	0.21	0.22	0.16	0.27	0.25
Max	0.23	0.19	0.17	0.19	0.27	0.15	0.20	0.18	0.25	0.19	0.17	0.19	0.22
Min	-0.46	-0.36	-0.31	-0.40	-0.31	-0.30	-0.36	-0.38	-0.26	-0.29	-0.18	-0.38	-0.36
Beta	0.83	0.76	0.73	0.71	0.64	0.63	0.68	0.68	0.70	0.67	-0.15	1.00	1.00
Sharpe Ratio	-0.15	0.07	-0.03	0.03	0.15	0.34	0.27	0.50	0.67	0.50	0.97	0.10	0.43
T-Value	-5.45	-0.85	-3.61	-2.15	1.00	6.35	4.20	9.40	11.79	8.38	7.65		
IR	-0.40	-0.09	-0.28	-0.18	0.02	0.27	0.21	0.58	0.84	0.53	0.36		
Panel C: Operating Profit-to-Enterprise Value													
Excess Returns	-0.03	-0.01	0.03	0.07	-0.01	0.06	0.06	0.05	0.07	0.16	0.20	0.03	0.11
Standard Deviation	0.25	0.28	0.26	0.24	0.21	0.21	0.18	0.20	0.20	0.21	0.14	0.27	0.25
Max	0.16	0.23	0.26	0.44	0.18	0.31	0.15	0.18	0.16	0.17	0.14	0.19	0.22
Min	-0.39	-0.40	-0.40	-0.32	-0.37	-0.35	-0.29	-0.33	-0.31	-0.30	-0.11	-0.38	-0.36
Beta	0.73	0.91	0.88	0.73	0.63	0.65	0.60	0.64	0.63	0.63	-0.10	1.00	1.00
Sharpe Ratio	-0.12	-0.03	0.10	0.28	-0.03	0.28	0.30	0.25	0.36	0.79	1.37	0.10	0.43
T-Value	-4.58	-3.47	-0.15	3.90	-2.86	3.96	4.99	3.69	6.01	12.29	10.60		
IR	-0.34	-0.24	-0.02	0.22	-0.22	0.20	0.19	0.16	0.32	0.88	0.50		
Panel D: EBIT-to-Enterprise Value													
Excess Returns	-0.02	-0.03	0.04	0.06	0.00	0.05	0.06	0.05	0.08	0.15	0.17	0.03	0.11
Standard Deviation	0.26	0.28	0.26	0.24	0.21	0.21	0.18	0.20	0.20	0.21	0.15	0.27	0.25
Max	0.17	0.23	0.26	0.44	0.21	0.32	0.16	0.15	0.19	0.17	0.16	0.19	0.22
Min	-0.40	-0.41	-0.38	-0.34	-0.37	-0.36	-0.28	-0.35	-0.30	-0.29	-0.11	-0.38	-0.36
Beta	0.76	0.93	0.86	0.73	0.64	0.63	0.60	0.64	0.65	0.64	-0.12	1.00	1.00
Sharpe Ratio	-0.08	-0.11	0.14	0.27	-0.01	0.23	0.32	0.27	0.41	0.73	1.18	0.10	0.43
T-Value	-3.85	-5.51	1.09	3.68	-2.36	2.83	5.49	4.17	6.96	11.77	9.30		
IR	-0.28	-0.39	0.06	0.22	-0.18	0.13	0.22	0.19	0.41	0.84	0.43		

The results support the findings on Table XI that decile portfolios sorted on Book-to-Market Equity earn inferior average alphas compared to decile portfolios sorted on income-generating items. On the overall, there is an increasing pattern in alphas earned from decile portfolio D1 to decile portfolio D10, confirming the existence of the Value anomaly in LatAm equities. Interestingly, the CAPM cannot explain entirely top decile portfolios sorted on market multiples unless the effect is being exploited using the Book-to-Market Equity and the Net Income-to-Market Equity ratio. Tables XIV and XV illustrate that when using Operating Profit-to-Enterprise Value and EBIT-to-Enterprise Value as a measure of valuation, long-only top decile portfolios that buy the cheapest stocks can generate, on average, monthly alphas of 0.73% and 0.63%, significant at the 1% and 5% level, respectively. It places value-sorted portfolios as the most potent effect reported so far in the targeted markets. Consequently, a strategy that buys cheap stocks and sells-short expensive stocks earn, on average, an alpha corresponding to more than one hundred basis points when the CAPM is employed as the asset pricing model.

Table XII
Regression Outputs for LatAm Decile Portfolios Based on Book-to-Market Equity

This table displays the regression outputs for ten decile portfolios formed based on Book-to-Market Equity. D1 contains the most expensive stocks, whereas D10 contains the cheapest stocks. D10-1 represents the cheap-minus-expensive strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-0.92*****	**-0.23**	**-0.59*****	-0.26	-0.35	0.02	-0.08	0.04	0.13	0.06	**0.98*****
RMRF	**0.78*****	**0.64*****	**0.76*****	**0.68*****	**0.68*****	**0.70*****	**0.66*****	**0.68*****	**0.74*****	**0.72*****	-0.06
Adj-R^2	0.70	0.71	0.74	0.71	0.65	0.66	0.68	0.68	0.68	0.55	0.01
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.29*****	**-0.60*****	**-0.96*****	**-0.79*****	**-0.75*****	**-0.56****	**-0.65*****	**-0.46****	**-0.41****	**-0.53****	**0.76****
RMRF	**0.91*****	**0.79*****	**0.92*****	**0.88*****	**0.81*****	**0.92*****	**0.86*****	**0.85*****	**0.91*****	**0.89*****	-0.01
SMB	**0.38*****	**0.43*****	**0.45*****	**0.59*****	**0.40*****	**0.63*****	**0.60*****	**0.52*****	**0.53*****	**0.55*****	0.17*
HML	**0.24*****	**0.13*****	0.02	**0.21*****	**0.31*****	**0.26*****	**0.33*****	**0.34*****	**0.48*****	**0.59*****	0.35***
Adj-R^2	0.75	0.76	0.77	0.80	0.72	0.76	0.80	0.78	0.81	0.71	0.11
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.19*****	**-0.45****	**-0.89*****	**-0.71*****	**-0.63*****	**-0.48****	**-0.55*****	**-0.38***	**-0.36***	**-0.47***	**0.72****
RMRF	**0.90*****	**0.78*****	**0.91*****	**0.88*****	**0.80*****	**0.91*****	**0.85*****	**0.85*****	**0.90*****	**0.89*****	-0.01
SMB	**0.37*****	**0.41*****	**0.44*****	**0.58*****	**0.39*****	**0.63*****	**0.59*****	**0.51*****	**0.52*****	**0.54*****	0.17*
HML	**0.18*****	0.03	-0.02	**0.16*****	**0.24*****	**0.21*****	**0.28*****	**0.29*****	**0.45*****	**0.55*****	**0.37*****
MOM	**-0.10****	**-0.15*****	**-0.07***	**-0.08****	**-0.12*****	**-0.08****	**-0.09*****	**-0.07****	-0.05	-0.06	0.04
Adj-R^2	0.75	0.78	0.78	0.81	0.73	0.76	0.81	0.79	0.81	0.71	0.11

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Unsurprisingly, when the SMB and HML are added as explanatory variables to the CAPM Model, all alphas reported decrease close to zero. For the Operating Profit-to-Enterprise Value top sorted portfolio (i.e., D10), the Fama-French Three-Factor Model is now enough to explain the cross-sectional average returns within the cheapest stocks in LatAm: Panel B of Table XIV shows that top decile portfolio D10 generates an average positive alpha of 0.19% per month, but not significant even at the 10% level. However, this strategy continues to be superior compared to other Value portfolios considered in this research. For instance, Panel B of Table XII indicates that the alpha for the top decile portfolio D10 reaches a negative value of 0.53% per month when stocks are sorted using the Book-to-Market Equity ratio. This result should be expected as the strategy uses the same underlying item employed to create the Value factor: HML gets large significant loadings on Book-to-Market Equity sorted portfolios. Therefore, the Fama-French Three-Factor Model is capable of reducing the alpha of the difference portfolio using this strategy. However, although the alpha is reduced, it continues to be statistically significant at the 5% level. For other strategies, it is surprising to evidence how the HML's loadings are low, and in most cases, not significant when using the Three-Factor Model. It means that by using other variables as a definition for valuation, an investor could enhance the Value effect.

Table XIII
Regression Outputs for LatAm Decile Portfolios Based on Net Income-to-Market Equity

This table displays the regression outputs for ten decile portfolios formed based on Net Income-to-Market Equity. D1 contains the most expensive stocks, whereas D10 contains the cheapest stocks. D10-1 represents the cheap-minus-expensive strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.05*****	**-0.51****	**-0.67*****	**-0.56*****	-0.29	-0.02	-0.14	0.23	**0.54****	0.30	**1.35*****
RMRF	**0.83*****	**0.76*****	**0.73*****	**0.71*****	**0.64*****	**0.63*****	**0.68*****	**0.68*****	**0.70*****	**0.68*****	**-0.16*****
Adj-R^2	0.59	0.72	0.72	0.74	0.59	0.74	0.70	0.71	0.67	0.62	0.06
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.77*****	**-0.99*****	**-0.98*****	**-1.00*****	**-0.73*****	**-0.42****	**-0.63*****	-0.26	0.01	-0.22	**1.55*****
RMRF	**1.08*****	**0.92*****	**0.83*****	**0.87*****	**0.81*****	**0.77*****	**0.87*****	**0.86*****	**0.87*****	**0.85*****	**-0.23*****
SMB	**0.76*****	**0.48*****	**0.32*****	**0.48*****	**0.49*****	**0.43*****	**0.55*****	**0.53*****	**0.54*****	**0.53*****	**-0.23****
HML	**0.44*****	**0.37*****	**0.21*****	**0.21*****	**0.19*****	**0.22*****	**0.21*****	**0.27*****	**0.42*****	**0.38*****	-0.06
Adj-R^2	0.70	0.81	0.76	0.80	0.65	0.81	0.79	0.80	0.80	0.72	0.07
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.61*****	**-0.93*****	**-0.89*****	**-0.88*****	**-0.60****	**-0.33****	**-0.54*****	-0.20	0.06	-0.20	**1.40*****
RMRF	**1.07*****	**0.91*****	**0.83*****	**0.87*****	**0.80*****	**0.77*****	**0.86*****	**0.85*****	**0.87*****	**0.85*****	**-0.22*****
SMB	**0.74*****	**0.47*****	**0.31*****	**0.47*****	**0.47*****	**0.42*****	**0.54*****	**0.52*****	**0.53*****	**0.53*****	**-0.21****
HML	**0.33*****	**0.34*****	**0.16*****	**0.13*****	**0.11***	**0.16*****	**0.15*****	**0.23*****	**0.38*****	**0.36*****	0.03
MOM	**-0.17*****	-0.06	**-0.09****	**-0.12*****	**-0.13*****	**-0.09*****	**-0.09****	**-0.07***	-0.05	-0.02	**0.15****
Adj-R^2	0.71	0.81	0.76	0.81	0.66	0.82	0.79	0.81	0.80	0.72	0.09

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

When we use the Carhart Four-Factor Model to explain the average cross-sectional returns in Value-sorted portfolios, there is no material effect on the generated alphas concerning the regression outputs for the Fama-French Three-Factor Model. As in the other two models used, bottom decile portfolios experience negative alphas that cannot be explained by all the explanatory variables together. There is an increasing pattern in the alphas, but most of them are still negative and significant. As previously noted, the cheapest stocks sorted on Operating Profit-to-Enterprise Value, and EBIT-to-Enterprise Value still earns a positive but not significant alpha. Thus, the Carhart Model can explain long-only top deciles portfolios that invest exclusively in cheap companies in LatAm. Interestingly, risk factors' loadings in the Four-Factor Model, although significant, are relatively low. It means that Value-sorted portfolios cannot be characterized severely by any of the underlying firms' characteristics implied by the factors. Most cheap stocks are not mainly represented only by small-caps. Additionally, these Value firms do not exhibit Momentum characteristics at all. In fact, in all strategies described, MOM's loadings are slightly negative meaning that cheap/expensive stocks do not exhibit a Momentum effect. This evidence can have significant implications from a strategy creation setting: combining Value and Momentum could bring impressive results for an active investor.

Table XIV
Regression Outputs for LatAm Decile Portfolios Based on Operating Profit-to-Enterprise Value

This table displays the regression outputs for ten decile portfolios formed based on Operating Profit-to-Enterprise Value. D1 contains the most expensive stocks, whereas D10 contains the cheapest stocks. D10-1 represents the cheap-minus-expensive strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	-0.87***	-0.86***	-0.54**	-0.08	-0.59**	-0.08	-0.06	-0.14	0.04	0.73***	1.60***
RMRF	0.74***	0.92***	0.89***	0.73***	0.63***	0.65***	0.60***	0.65***	0.63***	0.63***	-0.11***
Adj-R^2	0.55	0.67	0.74	0.61	0.58	0.63	0.69	0.68	0.65	0.60	0.03
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	-1.48***	-1.18***	-0.96***	-0.69***	-1.09***	-0.61***	-0.49***	-0.59***	-0.49***	0.19	1.66***
RMRF	0.95***	1.02***	1.02***	0.95***	0.81***	0.86***	0.76***	0.80***	0.81***	0.82***	-0.13***
SMB	0.64***	0.33***	0.42***	0.67***	0.54***	0.59***	0.49***	0.47***	0.55***	0.56***	-0.08
HML	0.37***	0.25***	0.34***	0.28***	0.26***	0.17***	0.17***	0.27***	0.34***	0.37***	-0.01
Adj-R^2	0.65	0.70	0.80	0.70	0.67	0.71	0.77	0.76	0.78	0.72	0.02
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	-1.36***	-1.18***	-0.90***	-0.63**	-0.93***	-0.47**	-0.39**	-0.46**	-0.37**	0.25	1.61***
RMRF	0.94***	1.02***	1.02***	0.95***	0.80***	0.85***	0.76***	0.79***	0.81***	0.81***	-0.13**
SMB	0.62***	0.32***	0.41***	0.66***	0.52***	0.58***	0.48***	0.45***	0.54***	0.55***	-0.07
HML	0.30***	0.24***	0.31***	0.24***	0.16***	0.09	0.10**	0.19***	0.27***	0.33***	0.03
MOM	-0.12**	-0.01	-0.06	-0.06	-0.16***	-0.13***	-0.10***	-0.12***	-0.12***	-0.06	0.05
Adj-R^2	0.66	0.70	0.80	0.70	0.69	0.72	0.78	0.78	0.79	0.72	0.02

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Meanwhile, the difference portfolio still earns a significant alpha after correcting for all four systematic risk factors. Although it is slightly reduced compared to the other two models employed, it generates an astonishing average excess return of more than one-hundred and fifty basis points per month. These results are then consistent with the hypotheses of the existence of a Value anomaly in LatAm. Summing up, we find that the traditional definition of Value through the use of the Book-to-Market Equity ratio exhibits inferior average excess returns compared to the strategies that use income-generating items and the Enterprise Value as a measure of valuation. For these value-sorted portfolios, a long-only strategy that invests in the top decile portfolio cannot be explained entirely by the Market portfolio and could be used to beat the RMRF, which is quite high in our data sample. More importantly, if we compare the average excess return of all value-sorted portfolios, including those in Table XII, an active investor could beat a passive investment strategy that replicates the MSCI Emerging Markets Latin America Index. The difference in performance is significant even in middle decile portfolios sorted on Value.

Table XV
Regression Outputs for LatAm Decile Portfolios Based on EBIT-to-Enterprise Value

This table displays the regression outputs for ten decile portfolios formed based on EBIT-to-Enterprise Value. D1 contains the most expensive stocks, whereas D10 contains the cheapest stocks. D10-1 represents the cheap-minus-expensive strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-0.81****	**-1.06*****	**-0.44***	-0.11	**-0.56****	-0.15	-0.03	-0.11	0.11	**0.63****	**1.45*****
RMRF	**0.76*****	**0.93*****	**0.86*****	**0.74*****	**0.64*****	**0.64*****	**0.61*****	**0.64*****	**0.65*****	**0.64*****	**-0.12*****
Adj-R^2	0.56	0.69	0.73	0.61	0.57	0.61	0.69	0.67	0.65	0.61	0.04
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.4*****	**-1.41*****	**-0.83*****	**-0.74*****	**-1.05*****	**-0.72*****	**-0.43****	**-0.59*****	**-0.42****	0.13	**1.52*****
RMRF	**0.96*****	**1.05*****	**0.99*****	**0.96*****	**0.83*****	**0.86*****	**0.76*****	**0.82*****	**0.83*****	**0.81*****	**-0.15*****
SMB	**0.61*****	**0.35*****	**0.38*****	**0.69*****	**0.55*****	**0.65*****	**0.45*****	**0.52*****	**0.55*****	**0.52*****	-0.09
HML	**0.39*****	**0.26*****	**0.34*****	**0.32*****	**0.22*****	**0.19*****	**0.17*****	**0.25*****	**0.37*****	**0.37*****	-0.02
Adj-R^2	0.65	0.72	0.79	0.72	0.65	0.71	0.76	0.77	0.78	0.73	0.03
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.29*****	**-1.41*****	**-0.75*****	**-0.67*****	**-0.88*****	**-0.59*****	**-0.33***	**-0.47****	-0.31	0.18	**1.47*****
RMRF	**0.95*****	**1.05*****	**0.98*****	**0.96*****	**0.82*****	**0.85*****	**0.75*****	**0.81*****	**0.83*****	**0.81*****	**-0.15*****
SMB	**0.59*****	**0.35*****	**0.38*****	**0.68*****	**0.53*****	**0.64*****	**0.44*****	**0.51*****	**0.54*****	**0.51*****	-0.08
HML	**0.31*****	**0.26*****	0.29***	**0.28*****	**0.11***	**0.10***	**0.11****	**0.18*****	**0.29*****	**0.33*****	0.02
MOM	**-0.11****	0.01	**-0.08***	-0.07	**-0.17*****	**-0.14*****	**-0.10*****	**-0.12*****	**-0.12*****	-0.06	0.06
Adj-R^2	0.66	0.72	0.79	0.72	0.67	0.72	0.77	0.78	0.79	0.73	0.03

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

6.2.3 Low-beta and low-volatility strategies

Table XVI displays the summary statistics for 20 decile portfolios based on past volatility and beta levels. For a time horizon of one year, portfolios that contain the least (D10) volatile stocks outperform portfolios that contain the most volatile (D1) stocks as measured by both annualized excess returns and Sharpe ratios. Similarly, bottom decile portfolios exhibit a higher standard deviation than top decile portfolios. Portfolios sorted on beta show a regular increasing pattern in excess returns from D1 to D10 compared to portfolios sorted on idiosyncratic volatility. Table XVI Panel B illustrates that portfolio D10 experiences lower excess returns than portfolios D9 and D8. However, portfolios sorted on idiosyncratic volatility earn higher Sharpe ratios than portfolios sorted on beta. This could be since beta, as a sorted variable, tends to be more volatile than idiosyncratic volatility, which makes beta sorted portfolios riskier (i.e., higher standard deviation). Furthermore, one common attribute of both strategies is that the bottom decile portfolio earns a negative excess return, making profitable a strategy consisting of selling high risky stocks and buying low risky stocks. Consequently, we report evidence of a Low Volatility effect in LatAm equity markets.

It is also worth mentioning here that none long-only portfolio beats the RMRF factor, but if one takes into account a passive strategy for both a retail or institutional investor wanting to have exposure to LatAm equity markets through the use of an ETF that replicates the behavior of the MSCI Emerging Markets Latin America Index, then the implementation of either a low beta strategy or a Low Volatility strategy would enhance the risk-return tradeoff of an indexed strategy, even by managing a portfolio based on top decile firms only. The execution of a difference portfolio is not the only way to take advantage of the Low Volatility effect in the LatAm universe. These results are in line with the findings of Haugen and Heins (1972) and Blitz and van Vliet (2007) who show that more volatile funds and stocks exhibit lower average rates of return. Our results differ from the latter mainly as we use all the firms in the sample independent of size. Blitz and van Vliet (2007) only use large-cap stocks to make their results more conservative. Also, they use weekly returns to sort firms based on the last three years idiosyncratic volatility compared to the one-year idiosyncratic dispersion used in this research based on monthly returns. Despite the differences, this research shows that the Low Volatility and low beta effect are robust even when using small-caps and large-caps simultaneously and different definitions of idiosyncratic risk.

Table XVI
Descriptive Statistics for β and Volatility Sorted Portfolios

This table reports the descriptive statistics for twenty decile portfolios sorted on low-β and low idiosyncratic volatility. LATAM breakpoints are used when sorting on low-β and low-volatility stocks. D1 contains the stocks with the highest β/volatility, whereas D10 contains stocks with the lowest β/volatility. D10-1 represents the lowest β/volatility minus highest β/volatility strategy. β is the slope of the regression of last year monthly returns of firm i concerning the RMRF; while volatility is defined as the annualized standard deviation of last year monthly return of firm i. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio (IR). Beta is the slope of the regression between the returns of each decile portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe ratio of each decile portfolio and the BMK's Sharpe ratio. Data for the risk-free rate are taken from the Kenneth French library. Excess returns are the returns over the 1-month U.S T-Bill. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1	BMK	RMRF
Panel A: Low Beta													
Excess Returns	-0.03	0.03	0.06	0.06	0.05	0.07	0.09	0.04	0.06	0.06	0.10	0.03	0.11
Standard Deviation	0.38	0.31	0.27	0.24	0.21	0.18	0.17	0.17	0.16	0.16	0.32	0.27	0.25
Max	0.31	0.27	0.25	0.17	0.20	0.13	0.13	0.13	0.21	0.29	0.34	0.19	0.22
Min	-0.52	-0.47	-0.41	-0.42	-0.39	-0.31	-0.32	-0.35	-0.23	-0.18	-0.29	-0.38	-0.36
Beta	1.25	1.08	0.92	0.83	0.68	0.58	0.51	0.45	0.32	0.35	-0.90	1.00	1.00
Sharpe Ratio	-0.09	0.10	0.23	0.24	0.23	0.37	0.54	0.23	0.36	0.40	0.31	0.10	0.43
T-Value	-4.94	-0.05	3.42	4.44	2.74	6.28	8.55	2.35	3.94	4.66	1.68		
IR	-0.36	0.03	0.31	0.30	0.11	0.23	0.38	0.06	0.12	0.15	0.12		
Panel B: Low Volatility													
Excess Returns	-0.03	0.04	0.07	0.05	0.04	0.06	0.07	0.08	0.09	0.05	0.08	0.03	0.11
Standard Deviation	0.33	0.31	0.27	0.25	0.23	0.21	0.18	0.17	0.15	0.13	0.29	0.27	0.25
Max	0.30	0.27	0.21	0.19	0.18	0.17	0.14	0.13	0.12	0.12	0.29	0.19	0.22
Min	-0.47	-0.50	-0.37	-0.40	-0.37	-0.40	-0.29	-0.32	-0.23	-0.22	-0.28	-0.38	-0.36
Beta	1.02	1.04	0.92	0.86	0.74	0.71	0.59	0.55	0.44	0.25	-0.78	1.00	1.00
Sharpe Ratio	-0.09	0.12	0.26	0.21	0.19	0.29	0.39	0.42	0.58	0.39	0.27	0.10	0.43
T-Value	-4.28	0.43	4.58	2.84	2.17	4.75	7.06	7.31	9.22	4.18	1.40		
IR	-0.31	0.06	0.39	0.39	0.24	0.12	0.25	0.28	0.29	0.32	0.10		

Tables XVII and XVIII show the regression outputs for the one-year beta, and one-year idiosyncratic volatility sorted portfolios on the CAPM Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model. There is an ascending pattern in the generated alphas after controlling for systematic risk factors in both strategies. However, top decile portfolios earn in some cases, positive alphas that are not statistically significant. On the overall, none factor model can explain the negative alphas generated by all bottom decile portfolios. Consequently, a zero-cost strategy that buys the lowest risky stocks and sells the highest risky stocks simultaneously experiences significant positive alphas that cannot be explained by traditional risk factors. This evidence contradicts the generally accepted wisdom that higher returns should always compensate for higher risk. Additionally, sorting stocks based on idiosyncratic volatility is more challenging for asset pricing models as the cross-sectional average returns are broader compared to sorting stocks based on market-β.

Panel A of Tables XVII and XVIII illustrates that the RMRF's loading decreases as expected from D1 to D10 as top decile portfolios are less correlated to the Market portfolio. The CAPM by itself leaves much of the cross-sectional variation in expected returns unexplained in most top decile portfolios as their alphas are still positive but insignificant, and their Adj-R^2 are below 50% in both strategies. Unsurprisingly, when the CAPM is augmented with SMB and HML, top decile portfolios' alphas are now closer to zero, especially for top decile portfolios. HML loadings are significantly positive for bottom decile portfolios, but not for top decile portfolios. This pattern is consistent in both strategies, which means that high risky stocks exhibit a Value tilt compared to less risky stocks. Loadings on SMB are strangely different for β-sorted portfolios than for volatility-sorted portfolios. For the former, SMB loadings increase monotonically from D1 to D10. It implies that for β-sorted portfolios, less risky stocks are mainly represented by small-cap firms, which is surprising given the notion that small-caps are considered the riskiest. Panel B of Table XVII shows that the difference portfolio's returns are neither driven by small-cap firms nor by large-cap stocks. Contrarily, in Panel B of Table XVIII, SMB loadings decrease consistently from D1 to D10. In this case, risky stocks are dominated mainly by small firms. However, SMB loadings on top decile portfolios are still positive and indicate the presence of Size effect in "safer" stocks.

Table XVII

Regression Outputs for LatAm Decile Portfolios Based on One-Year β

This table displays the regression outputs for ten decile portfolios formed based on one-year market-β. D1 contains the stocks with the highest betas, whereas D10 contains the stocks with the lowest betas. D10-1 represents the lowest beta-minus-highest beta strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.35*****	**-0.66****	-0.27	-0.19	-0.21	0.02	0.31	0.05	0.19	0.20	**1.56*****
RMRF	**1.25*****	**1.08*****	**0.92*****	**0.83*****	**0.67*****	**0.59*****	**0.51*****	**0.45*****	**0.32*****	**0.35*****	**-0.90*****
Adj-R^2	0.70	0.77	0.72	0.75	0.68	0.69	0.57	0.43	0.27	0.33	0.51
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.92*****	**-1.13*****	**-0.87*****	**-0.71*****	**-0.73*****	**-0.44*****	-0.25	**-0.52****	-0.24	-0.24	**1.67*****
RMRF	**1.38*****	**1.20*****	**1.11*****	**1.01*****	**0.88*****	**0.76*****	**0.73*****	**0.64*****	**0.49*****	**0.54*****	**-0.84*****
SMB	**0.45*****	**0.40*****	**0.58*****	**0.54*****	**0.61*****	**0.52*****	**0.65*****	**0.55*****	**0.49*****	**0.54*****	0.09
HML	**0.84*****	**0.61*****	**0.53*****	**0.32*****	**0.09***	**0.16*****	**0.14*****	**0.14****	**0.13****	0.07	**-0.78*****
Adj-R^2	0.80	0.85	0.83	0.82	0.76	0.79	0.71	0.53	0.37	0.44	0.63
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.68*****	**-0.98*****	**-0.73*****	**-0.61*****	**-0.62*****	**-0.36****	**-0.18**	**-0.47***	-0.20	-0.28	**1.39*****
RMRF	**1.36*****	**1.19*****	**1.10*****	**1.00*****	**0.88*****	**0.76*****	**0.73*****	**0.63*****	**0.49*****	**0.54*****	**-0.82*****
SMB	**0.42*****	**0.39*****	**0.56*****	**0.53*****	**0.60*****	**0.51*****	**0.64*****	**0.54*****	**0.49*****	**0.54*****	0.12
HML	**0.69*****	**0.52*****	0.44***	**0.26*****	0.02	**0.10****	**0.09***	0.10	0.11	0.09	**-0.60*****
MOM	**-0.24*****	**-0.15*****	**-0.14*****	**-0.10*****	**-0.10*****	**-0.08*****	**-0.07****	-0.05	-0.04	0.04	**0.28*****
Adj-R^2	0.81	0.86	0.84	0.83	0.77	0.79	0.72	0.53	0.37	0.44	0.65

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Panel B of Table XVIII also illustrates that for the difference portfolio, all systematic risk factors load negatively. In other words, a strategy that buys less risky stocks and short sells high risky stocks is represented mainly by large-cap firms and growth companies. That is the reason why both SMB and HML cannot explain the cross-sectional average returns of the difference portfolio. Furthermore, the alpha reported in this strategy is more significant compared to previous strategies as the systematic risk factors do not share the characteristics of a Low Volatility portfolio. Finally, when the MOM factor is added to explain average returns of low-risk stocks, the explanatory power of the previous two asset pricing models is enhanced: decile portfolios' alphas are closer to zero. For both strategies, the negative alphas in bottom deciles portfolios can be explained partly by negative loadings on MOM. It implies that risky stocks usually are characterized by exhibiting a negative Momentum compared to top decile portfolios whose loadings to MOM are positive but insignificant. Looking at the difference portfolio in Panel C of Tables XVII and XVIII, the reduction in alpha compared to Panel B is since the difference portfolio's constituents present a Momentum effect, although it is not overly strong. Summing up, the Low-Volatility/Low-β effect is an anomaly that barely can be explained by common systematic risk factors.

Table XVIII
Regression Outputs for LatAm Decile Portfolios Based on One-Year Idiosyncratic Volatility

This table displays the regression outputs for ten decile portfolios formed based on one-year idiosyncratic volatility. D1 contains the stocks with the highest volatility, whereas D10 contains the stocks with the lowest volatility. D10-1 represents the lowest volatility-minus-highest volatility strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.12*** **	**-0.58***	-0.22	-0.31	-0.28	-0.10	0.06	0.12	**0.31***	0.19	**1.31*** **
RMRF	**1.03*** **	**1.05*** **	**0.93*** **	**0.86*** **	**0.74*** **	**0.71*** **	**0.59*** **	**0.56*** **	**0.44*** **	**0.25*** **	**-0.78*** **
Adj-R^2	0.61	0.71	0.76	0.74	0.68	0.70	0.70	0.65	0.57	0.25	0.45
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.89*** **	**-1.28*** **	**-0.73*** **	**-0.83*** **	**-0.76*** **	**-0.62*** **	**-0.34***	**-0.31***	-0.11	-0.17	**1.73*** **
RMRF	**1.28*** **	**1.27*** **	**1.08*** **	**1.02*** **	**0.91*** **	**0.90*** **	**0.75*** **	**0.73*** **	**0.60*** **	**0.39*** **	**-0.89*** **
SMB	**0.77*** **	**0.69*** **	**0.50*** **	**0.50*** **	**0.52*** **	**0.57*** **	**0.45*** **	**0.50*** **	**0.48*** **	**0.41*** **	**-0.36*** **
HML	**0.63*** **	**0.57*** **	**0.46*** **	**0.47*** **	**0.29*** **	**0.25*** **	**0.12*** **	**0.14*** **	**0.10*** **	**0.11** **	**-0.52*** **
Adj-R^2	0.72	0.82	0.84	0.83	0.76	0.79	0.77	0.74	0.68	0.35	0.52
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.64*** **	**-1.13*** **	**-0.61*** **	**-0.76*** **	**-0.67*** **	**-0.56*** **	-0.28	-0.25	-0.06	-0.11	**1.53*** **
RMRF	**1.26*** **	**1.26*** **	**1.08*** **	**1.02*** **	**0.90*** **	**0.89*** **	**0.74*** **	**0.72*** **	**0.60*** **	**0.39*** **	**-0.87*** **
SMB	**0.74*** **	**0.68*** **	**0.48*** **	**0.49*** **	**0.50*** **	**0.56*** **	**0.45*** **	**0.49*** **	**0.48*** **	**0.40*** **	**-0.34** **
HML	**0.46*** **	**0.48*** **	0.39***	**0.43*** **	**0.23*** **	**0.21*** **	**0.08***	**0.10** **	**0.07***	0.07	**-0.40*** **
MOM	**-0.26*** **	**-0.15*** **	**-0.12*** **	**-0.07***	**-0.10** **	**-0.06***	**-0.06***	**-0.06***	-0.05	-0.06	**0.20*** **
Adj-R^2	0.74	0.83	0.85	0.84	0.76	0.79	0.77	0.74	0.68	0.35	0.53

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

6.2.4 Quality strategies

Table XIX displays the summary statistics for 40 decile portfolios based on Quality definitions. We split the Quality score discussed in section 5.3.4 into three different criteria as defined by Asness, Frazzini, and Perdersen (2013). We form decile portfolios based on Profitability, Safety, and Growth in order to disentangle which Quality definition is the strongest in LatAm equity markets. Then, we combine them to form Quality decile portfolios as reported in Panel D of Table XIX. On the overall, a similar pattern in excess returns is evident across all Quality definitions. Returns increase from D1 to D10 and volatility follows an inverse path mainly for Profitability and Safety sorted portfolios. Panel A of Table XIX indicates that investors punish the least profitable stocks severely: decile portfolio D1 generates a negative average excess return of nearly 4% annually. For other Quality definitions, although the average excess return is not detrimental for this decile portfolio, it is the lowest among the other nine decile portfolios observed. Consequently, there is a rising effect in the Sharpe ratio. Top decile portfolios earn on average a higher average excess return at a lower risk than bottom decile portfolios do. This pattern creates the presence of a Quality-minus-Junk effect in LatAm equity markets, and it is consistent too with empirical evidence reported in the US and globally by Asness, Frazzini, and Perdersen (2013).

Interestingly, none top decile portfolio on Table XIX beat the RMRF in terms of average excess returns. However, the safest stocks represented by top decile portfolio D10 in Panel B earns a Sharpe ratio of 0.66, well above the 0.43 of the Market factor. Nevertheless, when sorted on Safety, the difference portfolio generates a Sharpe ratio even lower than decile portfolio D10. It is due to the high volatility experienced for this portfolio, as it is composed of short positions in stocks from decile portfolio D1, which is highly risky. On the other hand, the difference portfolio for stocks sorted on Profitability, Growth, and Quality generates abnormal risk-adjusted excess returns compared to the Market factor. More importantly, all top decile portfolios beat the MSCI Emerging Market Latin America Index in terms of both average excess returns and Sharpe ratios. It indicates that following a Quality strategy helps to create abnormal excess returns compared to a passive approach, and provides evidence against the Efficient Market Hypothesis (EMH) again. The four strategies (i.e., Momentum, Value, Low Volatility, and Quality) tested so far bring superior risk-adjusted excess returns compared to the Benchmark and supports the premise that emerging markets offer better opportunities due to more inefficiencies compared to the developed world.

Table XIX
Descriptive Statistics for Quality Sorted Portfolios

This Table reports the descriptive statistics for forty decile portfolios sorted on Profitability, Safety, Growth, and Quality. LATAM breakpoints are used when sorting on Quality stocks. D1 contains Junk stocks, whereas D10 contains Quality stocks. D10-1 represents the "Quality-minus-Junk" strategy for each category. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio (IR). Beta is the slope of the regression between the returns of each decile portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe ratio of each decile portfolio and the BMK's Sharpe ratio. Data for the risk-free rate are taken from the Kenneth French library. Excess returns are the returns over the 1-month U.S T-Bill. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1	Bmk	RMRF
Panel A: Profitability													
Excess Returns	-0.04	0.04	0.01	0.04	0.05	0.08	0.07	0.09	0.06	0.08	0.13	0.03	0.11
Standard Deviation	0.27	0.23	0.22	0.20	0.23	0.20	0.21	0.20	0.19	0.21	0.16	0.27	0.25
Max	0.22	0.16	0.19	0.15	0.29	0.18	0.18	0.24	0.14	0.17	0.14	0.19	0.22
Min	-0.46	-0.36	-0.37	-0.29	-0.38	-0.31	-0.32	-0.34	-0.28	-0.31	-0.20	-0.38	-0.36
Beta	0.84	0.74	0.74	0.63	0.74	0.67	0.70	0.66	0.64	0.66	-0.17	1.00	1.00
Sharpe Ratio	-0.15	0.16	0.05	0.18	0.23	0.39	0.33	0.43	0.34	0.39	0.82	0.10	0.43
T-Value	-5.82	1.27	-1.48	1.76	3.13	7.15	6.09	7.94	6.23	6.65	6.40		
IR	-0.44	0.06	-0.13	0.06	0.16	0.40	0.31	0.40	0.30	0.38	0.28		
Panel B: Safety													
Excess Returns	0.01	0.01	-0.01	0.06	0.06	0.06	0.07	0.05	0.09	0.09	0.08	0.03	0.11
Standard Deviation	0.30	0.29	0.26	0.22	0.22	0.20	0.19	0.19	0.15	0.14	0.25	0.27	0.25
Max	0.22	0.24	0.22	0.19	0.25	0.21	0.15	0.17	0.19	0.23	0.25	0.19	0.22
Min	-0.37	-0.33	-0.40	-0.34	-0.37	-0.39	-0.33	-0.37	-0.26	-0.20	-0.19	-0.38	-0.36
Beta	0.97	1.00	0.87	0.75	0.73	0.66	0.59	0.61	0.44	0.30	-0.67	1.00	1.00
Sharpe Ratio	0.02	0.02	-0.05	0.28	0.26	0.27	0.35	0.25	0.60	0.66	0.33	0.10	0.43
T-Value	-2.10	-2.46	-4.04	4.90	4.05	4.19	5.34	3.65	9.12	8.25	1.84		
IR	-0.16	-0.19	-0.34	0.30	0.22	0.19	0.25	0.12	0.33	0.27	0.11		
Panel C: Growth													
Excess Returns	0.01	0.02	0.01	0.04	0.09	0.07	0.05	0.06	0.09	0.09	0.08	0.03	0.11
Standard Deviation	0.23	0.21	0.20	0.22	0.22	0.21	0.21	0.20	0.23	0.23	0.14	0.27	0.25
Max	0.26	0.17	0.13	0.29	0.26	0.16	0.16	0.17	0.20	0.19	0.14	0.19	0.22
Min	-0.31	-0.32	-0.27	-0.39	-0.36	-0.38	-0.28	-0.31	-0.36	-0.34	-0.17	-0.38	-0.36
Beta	0.71	0.67	0.61	0.74	0.71	0.68	0.71	0.68	0.73	0.72	0.01	1.00	1.00
Sharpe Ratio	0.04	0.08	0.06	0.17	0.41	0.32	0.25	0.28	0.39	0.41	0.57	0.10	0.43
T-Value	-1.45	-0.47	-0.89	1.86	7.30	5.64	4.10	4.76	6.41	6.90	4.81		
IR	-0.12	-0.07	-0.10	0.08	0.42	0.30	0.20	0.23	0.43	0.45	0.17		
Panel D: Quality													
Excess Returns	0.00	0.00	0.00	0.05	0.04	0.06	0.06	0.06	0.09	0.09	0.09	0.03	0.11
Standard Deviation	0.23	0.23	0.23	0.23	0.21	0.19	0.19	0.19	0.20	0.22	0.13	0.27	0.25
Max	0.20	0.17	0.24	0.25	0.15	0.18	0.16	0.15	0.18	0.19	0.12	0.19	0.22
Min	-0.30	-0.36	-0.39	-0.31	-0.34	-0.34	-0.36	-0.28	-0.33	-0.35	-0.13	-0.38	-0.36
Beta	0.70	0.73	0.77	0.76	0.67	0.62	0.64	0.62	0.66	0.73	0.03	1.00	1.00
Sharpe Ratio	-0.01	-0.01	0.02	0.24	0.20	0.33	0.30	0.34	0.46	0.40	0.71	0.10	0.43
T-Value	-2.66	-2.92	-2.33	3.54	2.37	5.56	5.11	5.86	8.19	7.33	6.26		
IR	-0.20	-0.23	-0.19	0.19	0.09	0.26	0.21	0.26	0.47	0.46	0.21		

Tables XX to XXIII report the regression outputs using the Capital Asset Pricing Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model. The CAPM by itself can explain mostly all top decile portfolios using different definitions of Quality. All alphas generated by top decile portfolios are close to zero, except for top decile portfolios sorted based on Safety. For this strategy, the CAPM is not able to explain the cross-sectional variation in average excess returns, and decile portfolios D9 and D10 produce a significant average alpha of 0.35% and 0.46% per month. This can be inferred as RMRF garners low loadings on these portfolios, meaning that the safest stocks in LatAm depict a low correlation to the Market risk factor. This result should be expected as the safest stocks must have a low beta concerning the Market portfolio according to the definition given by Asness, Frazzini, and Perdersen (2013). On the other hand, all bottom decile portfolios obtain very negative alphas after correcting for systematic risk, leaving an opportunity to exploit this inefficient by taking short positions in these firms. Thus, a strategy that buys Quality stocks and shorts sells Junk stocks cannot be explained at all by the CAPM. On average, this strategy generates an alpha of one hundred basis points per month at the 1% confidence level. The performance is stronger in companies sorted on Safety and Profitability.

Table XX

Regression Outputs for LatAm Decile Portfolios Based on Profitability

This table displays the regression outputs for ten decile portfolios formed based on Profitability. D1 contains the stocks of the least profitable companies, whereas D10 contains the stocks of the most profitable companies. D10-1 represents the most profitable-minus-least profitable strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-1.07*** **	**-0.34**	**-0.54** **	-0.24	-0.22	0.07	-0.05	0.13	-0.03	0.09	**1.16*** **
RMRF	**0.84*** **	**0.75*** **	**0.74*** **	**0.64*** **	**0.75*** **	**0.67*** **	**0.70*** **	**0.66*** **	**0.64*** **	**0.66*** **	**-0.18*** **
Adj-R^2	0.62	0.66	0.72	0.62	0.69	0.70	0.74	0.70	0.73	0.65	0.08
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.81*** **	**-0.87*** **	**-1.02*** **	**-0.71*** **	**-0.64*** **	**-0.43** **	**-0.51*** **	-0.29	**-0.39** **	-0.36	**1.44*** **
RMRF	**1.11*** **	**0.92*** **	**0.90*** **	**0.78*** **	**0.90*** **	**0.85*** **	**0.86*** **	**0.82*** **	**0.76*** **	**0.84*** **	**-0.27*** **
SMB	**0.80*** **	**0.53*** **	**0.50*** **	**0.47*** **	**0.47*** **	**0.53*** **	**0.50*** **	**0.46*** **	**0.37*** **	**0.51*** **	**-0.29*** **
HML	**0.39*** **	**0.43*** **	**0.35*** **	**0.39*** **	**0.17*** **	**0.27*** **	**0.25*** **	**0.21*** **	**0.26*** **	**0.17*** **	**-0.22*** **
Adj-R^2	0.74	0.77	0.82	0.73	0.74	0.80	0.82	0.77	0.80	0.72	0.14
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.66*** **	**-0.82*** **	**-0.94*** **	**-0.61*** **	**-0.52** **	**-0.31***	**-0.42** **	-0.24	**-0.33***	-0.31	**1.35*** **
RMRF	**1.10*** **	**0.91*** **	**0.90*** **	**0.78*** **	**0.90*** **	**0.84*** **	**0.86*** **	**0.81*** **	**0.76*** **	**0.83*** **	**-0.26*** **
SMB	**0.78*** **	**0.52*** **	**0.49*** **	**0.46*** **	**0.46*** **	**0.52*** **	**0.49*** **	**0.45*** **	**0.36*** **	**0.51*** **	**-0.28*** **
HML	**0.30*** **	**0.40*** **	**0.30*** **	**0.33*** **	0.10	**0.19*** **	**0.19*** **	**0.18*** **	**0.22*** **	**0.14** **	**-0.16** **
MOM	**-0.15*** **	-0.05	**-0.09** **	**-0.10** **	**-0.11*** **	**-0.12*** **	**-0.09*** **	-0.05	**-0.06** **	-0.06	**0.09***
Adj-R^2	0.75	0.77	0.82	0.73	0.75	0.81	0.82	0.77	0.80	0.72	0.15

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

According to Panel B of Tables XX to XXIII, the Fama-French Three-Factor Model does a better job in explaining the cross-sectional average excess returns of decile portfolios sorted on Quality. Particularly, alphas generated by top decile portfolios D9 and D10, when stocks are sorted on Safety, disappear. This would make sense as two more systematic factors are used to explain the cross-sectional variation in these strategies. SMB, HML, and RMRF help to jointly reduce the alphas reported on Panel A. However, it is essential to note that HML role is not critical as its loadings are small for most top decile portfolios. These results are consistent with Asness, Frazzini, and Perdersen (2013) who found that HML and QMJ are negatively correlated as the former is selecting stocks based on stock prices and the latter is buying and selling firms based on Quality characteristics. This is also in line with the notion that Value stocks have decreased due to negative fundamentals and bad prospects; while Quality stocks are generally profitable, safe, and growing companies. Quality bottom decile portfolios obtain significantly positive HML loadings, supporting the idea that Junk firms tend to be also cheap prospects in some cases. Now, results from Panel B also determine that Quality stocks not always tend to be small caps. Although SMB loadings are significant and positive, these are low mostly on top decile portfolios. For bottom decile portfolios or Junk stocks, SMB Loadings are higher, which means that some small caps do not stand to be profitable, safe, and growing companies.

Table XXI
Regression Outputs for LatAm Decile Portfolios Based on Safety

This table displays the regression outputs for ten decile portfolios formed based on Safety. D1 contains the stocks of the least safe companies, whereas D10 contains the stocks of the safest companies. D10-1 represents the safest-minus-least safe strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-0.77****	**-0.80*****	**-0.84*****	-0.14	-0.15	-0.11	0.04	-0.13	**0.35***	**0.46****	**1.24*****
RMRF	**0.98*****	**1.00*****	**0.87*****	**0.76*****	**0.73*****	**0.66*****	**0.59*****	**0.61*****	**0.44*****	**0.30*****	**-0.67*****
Adj-R^2	0.68	0.76	0.72	0.75	0.70	0.68	0.60	0.67	0.53	0.32	0.45
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.37*****	**-1.18*****	**-1.27*****	**-0.62*****	**-0.71*****	**-0.66*****	**-0.43****	**-0.61*****	-0.12	0.16	**1.53*****
RMRF	**1.16*****	**1.10*****	**0.99*****	**0.91*****	**0.94*****	**0.88*****	**0.76*****	**0.79*****	**0.63*****	**0.44*****	**-0.72*****
SMB	**0.57*****	**0.32*****	**0.39*****	**0.48*****	**0.63*****	**0.62*****	**0.51*****	**0.54*****	**0.55*****	**0.39*****	-0.18
HML	**0.55*****	**0.51*****	**0.48*****	**0.36*****	**0.23*****	**0.18*****	**0.23*****	**0.18*****	**0.11*****	-0.03	**-0.58*****
Adj-R^2	0.78	0.83	0.81	0.84	0.79	0.78	0.69	0.77	0.67	0.40	0.56
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.28*****	**-1.11*****	**-1.15*****	**-0.52*****	**-0.56*****	**-0.56*****	-0.33	**-0.52*****	-0.07	0.18	**1.45*****
RMRF	**1.15*****	**1.09*****	**0.98*****	**0.91*****	**0.93*****	**0.87*****	**0.76*****	**0.78*****	**0.62*****	**0.44*****	**-0.71*****
SMB	**0.56*****	**0.31*****	**0.38*****	**0.47*****	**0.61*****	**0.61*****	**0.50*****	**0.53*****	**0.54*****	**0.38*****	-0.18
HML	**0.49*****	**0.47*****	0.40***	**0.30*****	**0.14*****	**0.12****	**0.17*****	**0.12****	**0.08***	-0.04	**-0.54*****
MOM	**-0.09***	-0.07	**-0.12*****	**-0.10*****	**-0.15*****	**-0.09****	**-0.09****	**-0.09*****	-0.05	-0.02	0.07
Adj-R^2	0.78	0.83	0.81	0.84	0.80	0.78	0.70	0.77	0.67	0.39	0.56

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Adding MOM as an explanatory variable helps to reduce the alpha generated mainly in the bottom decile portfolios, although the reduction is not significant. In fact, the Adj-R^2 slightly increases from results in Panel B to Panel C. Therefore, MOM does not make a material contribution to the explanation of average excess returns on Quality portfolios. In all Quality decile portfolios, MOM loadings are small and not significant even at the 10% level. This phenomena is critical in top and bottom deciles portfolios. Thus, neither Quality stocks nor Junk stocks exhibit a Momentum effect. It seems that investors do not prefer to sell neither buy Junk and Quality stocks concurrently. Again, HML loadings on the Carhart Model are high and significant, mainly in the bottom decile portfolios or Junk stock. It validates the notion that investors prefer to continue paying higher prices for stocks with excellent Quality characteristics. A Quality-minus-Junk strategy keeps earning an outstanding alpha even after controlling for four different systematic risk factors. Surprisingly, for some Quality strategies, SMB and HML loadings are not even statistically significant at any confidence level, and in other cases, these factors' loadings are negative. Therefore, combining the Size, the Value, and even the Momentum effect with Quality could bring outstanding results for active investors.

Table XXII

Regression Outputs for LatAm Decile Portfolios Based on Growth

This table displays the regression outputs for ten decile portfolios formed based on Growth. D1 contains the stocks of the least growing companies, whereas D10 contains the stocks of the most growing companies. D10-1 represents the most growing-minus-least growing strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-0.53***	**-0.42***	**-0.41***	-0.31	0.12	-0.04	-0.18	-0.11	0.09	0.12	**0.65****
RMRF	**0.71*****	**0.67*****	**0.61*****	**0.74*****	**0.71*****	**0.69*****	**0.71*****	**0.68*****	**0.74*****	**0.72*****	0.01
Adj-R^2	0.59	0.64	0.60	0.70	0.67	0.71	0.75	0.72	0.64	0.65	0.00
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.09*****	**-0.96*****	**-0.80*****	**-0.74*****	-0.35	**-0.54*****	**-0.50*****	**-0.51*****	**-0.43***	-0.33	**0.76*****
RMRF	**0.89*****	**0.85*****	**0.74*****	**0.89*****	**0.88*****	**0.86*****	**0.82*****	**0.82*****	**0.94*****	**0.88*****	-0.01
SMB	**0.54*****	**0.54*****	**0.40*****	**0.46*****	**0.52*****	**0.52*****	**0.31*****	**0.42*****	**0.59*****	**0.48*****	-0.06
HML	**0.50*****	**0.39*****	**0.28*****	**0.27*****	**0.24*****	**0.32*****	**0.25*****	**0.24*****	**0.19*****	0.27***	**-0.23*****
Adj-R^2	0.72	0.77	0.68	0.76	0.75	0.81	0.79	0.78	0.71	0.72	0.04
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.04*****	**-0.86*****	**-0.72*****	**-0.60*****	-0.30	**-0.46****	**-0.41****	**-0.41****	-0.35	-0.28	**0.76*****
RMRF	**0.88*****	**0.84*****	**0.73*****	**0.88*****	**0.88*****	**0.85*****	**0.81*****	**0.82*****	**0.93*****	**0.88*****	-0.01
SMB	**0.54*****	**0.53*****	**0.39*****	**0.44*****	**0.51*****	**0.51*****	**0.30*****	**0.41*****	**0.58*****	**0.48*****	-0.06
HML	**0.47*****	**0.33*****	0.23***	**0.18*****	**0.21*****	**0.27*****	**0.19*****	**0.18*****	**0.14****	0.24***	**-0.23*****
MOM	-0.05	**-0.10*****	**-0.08***	**-0.15*****	-0.05	**-0.07****	**-0.09*****	**-0.10*****	**-0.08***	-0.05	0.00
Adj-R^2	0.72	0.77	0.68	0.78	0.75	0.81	0.80	0.79	0.71	0.72	0.04

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table XXIII
Regression Outputs for LatAm Decile Portfolios Based on Quality

This table displays the regression outputs for ten decile portfolios formed based on Quality. D1 contains Junk stocks, whereas D10 contains Quality stocks. D10-1 represents the Quality-minus-Junk strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D10-1
Panel A: Regression Against the CAPM											
Alpha	**-0.62****	**-0.65****	**-0.62*****	-0.21	-0.24	-0.01	-0.08	-0.02	0.18	0.09	**0.72*****
RMRF	**0.70*****	**0.73*****	**0.77*****	**0.77*****	**0.68*****	**0.63*****	**0.64*****	**0.62*****	**0.66*****	**0.73*****	0.03
Adj-R^2	0.60	0.66	0.74	0.71	0.68	0.67	0.72	0.70	0.68	0.70	0.00
Panel B: Regression Against the Fama-French Three-Factor Model											
Alpha	**-1.20*****	**-1.15*****	**-1.08*****	**-0.67*****	**-0.76*****	**-0.49*****	**-0.52*****	**-0.36***	-0.26	**-0.38***	**0.82*****
RMRF	**0.88*****	**0.90*****	**0.94*****	**0.94*****	**0.86*****	**0.80*****	**0.80*****	**0.74*****	**0.83*****	**0.90*****	0.01
SMB	**0.57*****	**0.50*****	**0.50*****	**0.51*****	**0.55*****	**0.51*****	**0.48*****	**0.36*****	**0.49*****	**0.50*****	-0.06
HML	**0.49*****	**0.38*****	**0.28*****	**0.22*****	**0.29*****	**0.28*****	**0.20*****	**0.19*****	**0.16*****	0.26***	**-0.23*****
Adj-R^2	0.74	0.76	0.81	0.77	0.78	0.77	0.79	0.75	0.74	0.77	0.05
Panel C: Regression Against the Carhart Four-Factor Model											
Alpha	**-1.13*****	**-1.02*****	**-0.98*****	**-0.61*****	**-0.69*****	**-0.37****	**-0.43****	-0.25	-0.18	-0.32	**0.81*****
RMRF	**0.88*****	**0.89*****	**0.93*****	**0.93*****	**0.86*****	**0.79*****	**0.80*****	**0.73*****	**0.82*****	**0.89*****	0.01
SMB	**0.56*****	**0.49*****	**0.48*****	**0.50*****	**0.55*****	**0.50*****	**0.47*****	**0.35*****	**0.49*****	**0.49*****	-0.06
HML	**0.45*****	**0.30*****	0.21***	**0.19*****	**0.25*****	**0.21*****	**0.15*****	**0.12*****	**0.11****	0.23***	**-0.22*****
MOM	-0.07	**-0.13*****	**-0.11*****	-0.06	**-0.07***	**-0.12*****	**-0.09*****	**-0.11*****	**-0.08****	-0.05	0.01
Adj-R^2	0.75	0.77	0.81	0.77	0.78	0.78	0.80	0.76	0.75	0.77	0.05

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

We have documented so far in this section empirical evidence of the presence of a Momentum, a Value, a Low Volatility/Beta, and a Quality effect in LatAm equity markets. We have illustrated that some strategies are stronger than others, but on the overall, all of them seem to challenge existing asset pricing models when considering not only the difference portfolio but also some long-only investments. For example, Value and Momentum strategies can even beat the Market factor and generate abnormal risk-adjusted returns when using long-only strategies. On the other hand, despite Low Volatility and Quality stocks do not generate higher average excess returns compared to the RMRF, when an investor looks at the Sharpe ratio some variation in these strategies can earn higher Sharpe ratios even with a less expected return. We also show that within each strategy, some definitions are better to exploit the underlying premise of the anomaly. For instance, the path of the past year return matters, and a Quality Momentum strategy delivers better results compared to Generic Momentum strategies. When assessing the Value effect, income-generating items such as net income and operating profit are better candidates for market valuation; while Low Volatility expressed as the past standard deviation of returns surpasses Low Beta strategies on a risk-adjusted point of view. All in all results from Table VI to Table XXIII support Hypothesis 2 that Value, Momentum, Low-Volatility, and Quality sorted portfolios can generate abnormal excess returns after controlling for systematic risks factors in LatAm equity markets.

6.3 *Creating multi-factor investment strategies*

Figure 4 illustrates the historical risk-return relationship among the Momentum, the Value, the Low Volatility, and the Quality effect in LatAm equities. It graphs the most robust anomaly definitions reported in Section 6.2. Therefore, the Value effect is represented by the performance of stocks sorted on Operating Profit-to-Enterprise Value, the Momentum effect corresponds to companies sorted on Quality Momentum, the Quality effect takes firms sorted jointly on Profitability, Safety, and Growth, and the Volatility effect takes firms sorted on Idiosyncratic Volatility. Figure 4 also compares all anomalies in terms of Sharpe ratio generation. The bubble's size represents the Sharpe ratio for each effect: the higher the size, the better the risk-return trade-off. In line with results reported so far, the Value and the Momentum effect are the strongest in LatAm equity markets, followed by the Quality and the Low Volatility effect. Regarding the risk-return trade-off, the Value and the Momentum effect generate the highest Sharpe ratio. Despite Quality and Volatility generate less excess returns compared to the Market, the Sharpe ratio generation ability is quite similar compared to the Market.

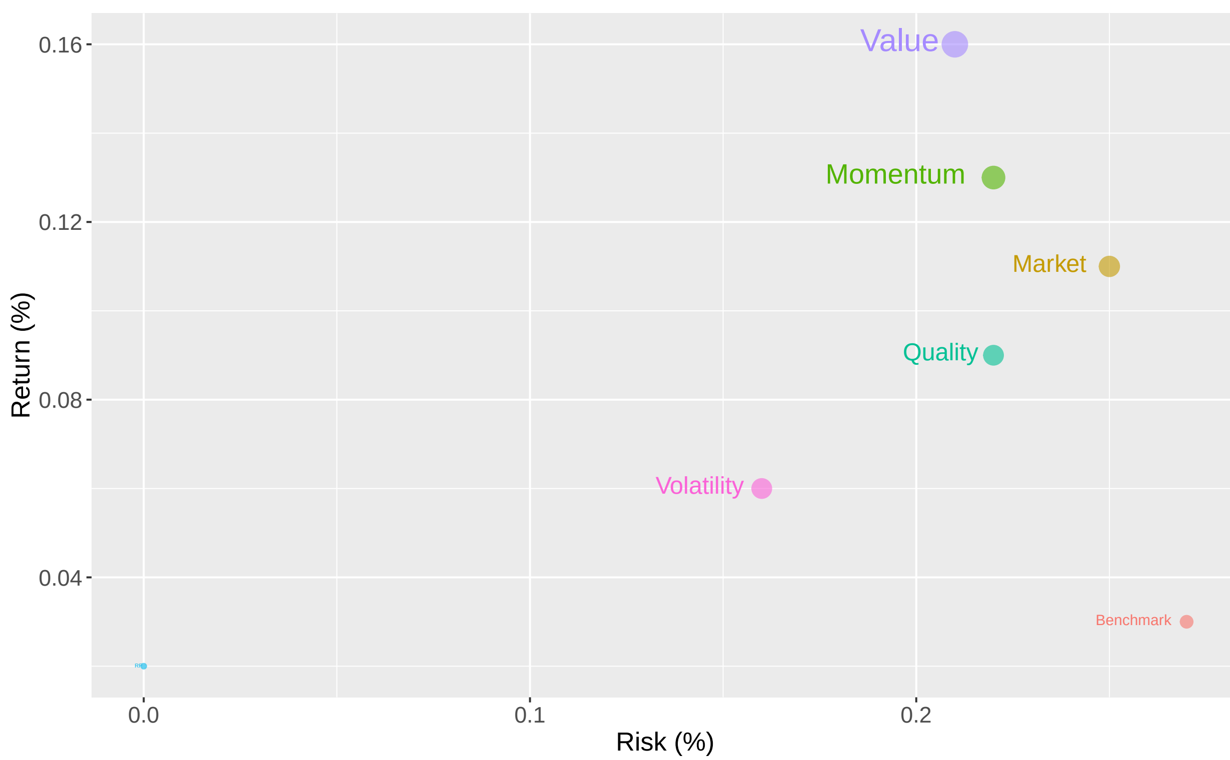

Figure 4
Historical risk-return trade-off of generic factors for LatAm equities. This figure shows the historical risk-return trade-off for the equally-weighted Momentum, Value, Low Volatility, and Quality effect in LatAm equity markets from January 2000 to December 2018. The size of the bubble corresponds to the Sharpe ratio among the anomalies. The higher the size, the better the risk-return trade-off.

Unsurprisingly, all effects that are shown in Figure 4 earn higher average excess returns with a lower risk compared to the MSCI Emerging Markets Latin America Index. Therefore, by actively selecting stocks based on past returns, valuation, Low Volatility, and Quality, an investor can significantly beat a passive strategy that invests entirely in the Benchmark. On the other hand, we can think of Momentum and Value as return-generating strategies while Volatility as a risk-controlled strategy. Consequently, an active investor could combine them to improve the risk-return trade-off depicted so far. Figure 5 shows the correlation coefficients among generic factors and the potential diversification benefits one could earn if two effects are put together. For instance, Quality is the least correlated anomaly among all effects with a neutral relation concerning Momentum and the Low Volatility. The Value effect also exhibits a low correlation concerning Momentum and Low Volatility.

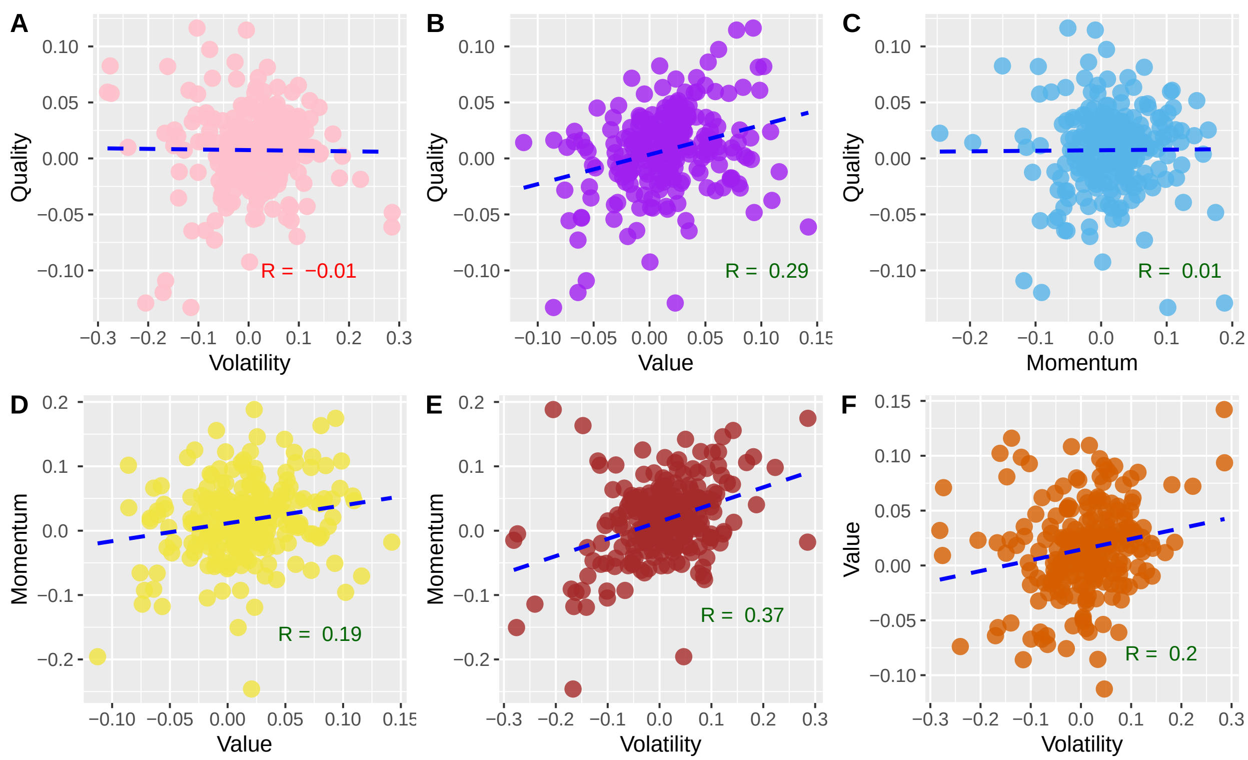

Figure 5
Scatter plots for generic factors returns. This Figure shows the relationships between pairs of generic factors returns. The blue-dashed line represents the best-fitting line among the data, and the R coefficient represents the correlation among generic factors. The return data spans from January 2000 to December 2018.

Section 9.3 in the Appendix also shows the annual returns for both long/short and long-only strategies based on Momentum, Value, Low Volatility, and Quality definitions from 2000 to 2018. We then compare the annual performance of these strategies with the performance of the Benchmark and the Market portfolio by painting the numbers with colors: whenever a figure is printed in green is due to outperformance and whenever a figure is printed in red is due to underperformance. Therefore, Tables XXXIX and XXXX illustrate that trading strategies have good and bad periods of performance, and that merely investing by using single-factors portfolios could generate sub-optimal results. For instance, Table XXXIX indicates that when the Market portfolio and the Benchmark have negative returns, long-short strategies perform particularly well. The opposite is also true. Thus, impatience investor would lose trust in the strategy that is being implemented. Furthermore, there are time intervals of consistent underperformance and outperformance, making the strategy less reliable. Table XXXX displays the performance of long-only portfolios compared to the Benchmark. There is a more consistent pattern in performance. However, Quality and Low Volatility lag in specific economic scenarios; while Momentum and Value tend to depict a better behavior in both bear and bull markets. Thereby, Figures 4 and 5, and Tables XXXIX and XXXX indicate that combining various single-factor strategies could generate better risk-return trade-offs as a low correlation among strategies is evident.

In this section, we report the diversification benefits of blending two or more strategies simultaneously. Seven portfolios are created to show the effects of combining Quality with Momentum, Value, and Low Volatility; Momentum with Value and Low Volatility; Value with Low Volatility; and, finally, a multifactor portfolio is constructed using all anomalies altogether. All portfolios are equally-weighted using a portfolio blending approach. We assess the attractiveness of collecting two or more strategies through the methodology developed by Gibbons, Ross, and Shanken (1989) known as the GRS test. Although this methodology seeks to evaluate the explanatory power of an asset pricing model, we employ this approach on both single-factor portfolios and multi-factor portfolios to determine which ones are the most challenging for the Capital Asset Pricing Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model when explaining average excess returns in LatAm equity markets. Gibbons, Ross, and Shanken (1989) also document how the GRS test is associated with improvements in the risk factors' Sharpe ratios: the higher the GRS statistic reported by the methodology, the more significant the improvement that could be obtained by joining together the risk factors with the test assets. Consequently, this approach will also help to determine whether the enhancement in the Sharpe ratios is more significant using single-factor portfolios or multi-factor portfolios.

6.3.1 GRS test on single- and multi-factor portfolios

Panel A of Table XXIV reports the summary statistics for the GRS test on the Capital Asset Pricing Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model on 40 Momentum, 40 Value, 20 Low Volatility, and 40 Quality portfolios. From there, it is evident that Momentum, Value, Low Volatility, and Quality portfolios can significantly improve the Sharpe ratio of risk factors. All GRS statistics reported in Panel A are high and significant at the 1% and 5% level; while $p-values$ are no higher than even 2%. The 40 Value and the 40 Quality portfolios are the ones that make the most considerable improvement in the Sharpe ratios: their GRS Statistics are the highest among the 140 portfolios tested in Panel A. Table XXIV provides other three important metrics which have important implications for the Efficient Market Hypothesis (EMH): θ_p represents the maximum Sharpe ratio of the n factor portfolios. For instance, the Sharpe ratio for the Market factor is 0.12; while the Sharpe ratio for the three factors represented by RMRF, SMB, and HML is 0.32. As expected, the Sharpe ratio for the four factors (i.e., including MOM) is the highest standing at 0.37. Contrarily, θ^* represents the slope of the efficient frontier based on all assets or the Sharpe ratio of all assets, including the risk factors. Therefore, when $\theta_p < \theta^*$ the risk-return trade-off of risk factors is lower than the same trade-off for all the assets, and we would have empirical evidence against the EMH that risk factors are not mean-variance efficient and that by adding Momentum, Value, Low Volatility, and Quality portfolios an investor could improve the investment outcome. Finally, θ_p/θ^* represents the proportion of the potential efficiency by adding the corresponding portfolios.

Metrics reported in Panel A of Table XXIV also supports the conclusions made in Section 6.2 that none of the asset pricing models employed in this research are able to explain the average monthly returns in Momentum, Value, Low Volatility, and Quality portfolios, but more importantly that investing using systematic and bias-free trading strategies could enhance the efficient investment universe in LatAm equity markets. In contrast, Panel B of Table XXIV (Continued) helps to test, statistically, whether reuniting different anomalies could bring diversification benefits than merely investing in a single-factor portfolio. Panel B reports the GRS Test statistics for 70 portfolios formed using a portfolio blending approach by mixing Momentum, Value, Low Volatility, and Quality equally. As in Panel A, all joint portfolios earn Sharpe ratios higher than the underlying risk factors', and there is a potential efficiency by using two or more strategies concurrently. Among the multi-factor portfolios considered, Momentum plus Value, Value Plus Low Volatility, and the Multifactor Portfolios are the ones with the best enhancement measured through the θ_p/θ^*. It is crucial mentioning here that the closer to zero the ratio, the better the potential efficiency.

Table XXIV
Summary Statistics for the GRS Test on Single- and Multi-factor Portfolios

This table reports the summary statistics for the GRS Test on the ability of the one-, the three-, and the four-factor model to explain the average monthly excess return on single- and multifactor-sorted portfolios. Panel A shows the statistics on 40 Momentum, 40 Value, 20 Low Volatility/Beta, and 40 Quality Portfolios. Panel B shows the statistics on 10 Multifactor Portfolios formed on equally-weighted pairs of Momentum, Value, Low Volatility, and Quality. The 10 Multifactor Portfolios equally combine Momentum, Value, Low Volatility, and Quality. The GRS Stat is the statistic for the test of the efficiency of a given portfolio(s). θ^* represents the slope of the efficient frontier based on all assets. θ_p represents the maximum Sharpe ratio of the n factor portfolios. θ_p/θ^* represents the proportion of potential efficiency.

Panel A: Single-Sorted Portfolios

	GRS Stat	P-Vaue	θ^*	θ_p	θ_p/θ^*		GRS Stat	P-Vaue	θ^*	θ_p	θ_p/θ^*
Panel A.1: 40 Momentum Portfolios						**Panel A.3: 20 Low Volatility Portfolios**					
RMRF	**1.73*****	0.84%	0.62	0.12	0.19	RMRF	**1.95****	1.10%	0.45	0.12	0.26
RMRF SMB HML	**2.21*****	0.02%	0.79	0.32	0.41	RMRF SMB HML	**2.56*****	0.05%	0.61	0.32	0.52
RMRF SMB HML MOM	**2.12*****	0.05%	0.81	0.37	0.46	RMRF SMB HML MOM	**2.16*****	0.38%	0.61	0.37	0.61
Panel A.2: 40 Value Portfolios						**Panel A.4: 40 Quality Portfolios**					
RMRF	**3.13*****	0.00%	0.83	0.12	0.14	RMRF	**2.51*****	0.00%	0.74	0.12	0.16
RMRF SMB HML	**3.15*****	0.00%	0.92	0.32	0.35	RMRF SMB HML	**2.92*****	0.00%	0.89	0.32	0.36
RMRF SMB HML MOM	**2.89*****	0.00%	0.92	0.37	0.41	RMRF SMB HML MOM	**2.68*****	0.00%	0.89	0.37	0.42

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table XXIV (Continued)

Summary Statistics for the GRS Test on Single- and Multi-factor Portfolios

This table reports the summary statistics for the GRS Test on the ability of one-, three-, and four-factor models to explain the average monthly excess return on single- and multifactor-sorted portfolios. Panel A shows the statistics on 40 Momentum, 40 Value, 20 Low Volatility/Beta, and 40 Quality Portfolios. Panel B shows the statistics on 10 Multifactor Portfolios formed on equaly-weighted pairs of Momentum, Value, Low Volatility, and Quality. The 10 Multifactor Portfolios equally combine Momentum, Value, Low Volatility, and Quality. The GRS Stat is the statistic for the test of the efficiency of a given portfolio(s). θ^* represents the slope of the efficient frontier based on all assets. θ_p represents the maximum Sharpe ratio of the n factor portfolios. θ_p/θ^* represents the proportion of potential efficiency.

Panel B: Multifactor-Sorted Portfolios

	GRS Stat	P-Vaue	θ^*	θ_p	θ_p/θ^*
Panel B.1: 10 Quality + Low Vol Portfolios					
RMRF	**3.11*****	0.10%	0.40	0.12	0.30
RMRF SMB HML	**6.10*****	0.00%	0.64	0.32	0.50
RMRF SMB HML MOM	**5.25*****	0.00%	0.64	0.37	0.58
Panel B.2: 10 Quality + Momentum Portfolios					
RMRF	**3.45*****	0.03%	0.42	0.12	0.29
RMRF SMB HML	**4.92*****	0.00%	0.59	0.32	0.54
RMRF SMB HML MOM	**4.06*****	0.00%	0.59	0.37	0.63
Panel B.3: 10 Momentum + Low Vol Portfolios					
RMRF	**3.81*****	0.01%	0.44	0.12	0.27
RMRF SMB HML	**5.47*****	0.00%	0.61	0.32	0.52
RMRF SMB HML MOM	**4.58*****	0.00%	0.62	0.37	0.61
Panel B.4: 10 Multifactor Portfolios					
RMRF	**6.24*****	0.00%	0.55	0.12	0.22
RMRF SMB HML	**6.54*****	0.00%	0.66	0.32	0.49
RMRF SMB HML MOM	**5.80*****	0.00%	0.66	0.37	0.56
Panel B.5: 10 Quality + Value Portfolios					
RMRF	**5.32*****	0.00%	0.51	0.12	0.23
RMRF SMB HML	**6.77*****	0.00%	0.67	0.32	0.48
RMRF SMB HML MOM	**6.10*****	0.00%	0.68	0.37	0.55
Panel B.6: 10 Momentum + Value Portfolios					
RMRF	**5.02*****	0.00%	0.50	0.12	0.24
RMRF SMB HML	**5.21*****	0.00%	0.60	0.32	0.53
RMRF SMB HML MOM	**4.39*****	0.00%	0.61	0.37	0.62
Panel B.7: 10 Value + Low Vol Portfolios					
RMRF	**5.63*****	0.00%	0.52	0.12	0.23
RMRF SMB HML	**6.14*****	0.00%	0.64	0.32	0.50
RMRF SMB HML MOM	**5.33*****	0.00%	0.65	0.37	0.58

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

In fact, using all four strategies synchronously brings the best risk-return trade-off among all strategies reported in Panel B. We can assess whether an investment strategy is better than another by looking at the size of the GRS statistic. As mentioned previously, the higher its value, the more significant the upturn. Consequently, multi-factor portfolios are placed as more challenging for traditional asset pricing models than single-factor portfolios. The GRS statistics in Panel B are much higher than the GRS statistics reported in Panel A of Table XXIV even though θ^* is lower and θ_p/θ^* higher in multi-factor portfolios than in single-factor portfolios. The reason is that the GRS Statistic places much weight into the potential benefits of reducing the variation in average monthly returns when test assets are combined with the risk factors than the other two metrics. With this evidence, we can statistically test Hypothesis 3, which states that multi-factor portfolios can significantly improve the performance of single-factor portfolios due to diversification benefits in LatAm equity markets. Our results are consistent with previous literature that test the potential benefits of merging anomalies in other markets and asset classes. For instance, Houweling and van Zundert (2014) show that an equally-weighted multi-factor portfolio in the corporate debt market delivers a lower tracking error and a higher information ratio than individual long-only factor portfolios. This research differentiates itself as it illustrates the diversification benefits of merging not only all factors simultaneously, but also reporting the benefits of combining only two investment strategies.

6.3.2 Portfolio blending approach vs signal blending approach

Table XXV also brings further empirical evidence of the importance of combining two or more strategies in the improvement of Sharpe ratios. It reports the performance statistics of long-only portfolios formed by using both a portfolio blending approach and a signal blending approach. Performance statistics for long-only portfolios are reported as we want to determine whether an investor that has short-sell restrictions could even benefit from mixing strategies by taking long positions in stocks or portfolios that share the characteristics of two or more strategies. From a practical point of view, this means that investors could beat the Benchmark and Market portfolio without having to use leverage or taking short-sell positions that most of the time are difficult to build and hold. To recap, Section 6.2 reports that all considered anomalies generate average excess returns and Sharpe ratios above the Benchmark. However, not all top decile portfolios (i.e., long-only single-factor portfolios) beat the Market portfolio by neither average excess returns nor by Sharpe Ratio generation. Hence, Table XXV also records empirical evidence in favor of Hypothesis 3 just tested in the last Section that multi-factor portfolios can significantly improve the performance of single-factor portfolios.

Even though not all multi-factor portfolios reported in Table XXV beat the Market portfolio in terms of average excess returns, all of them beat the Market portfolio when considering the Sharpe ratio. By combining two or more anomalies, an active investor could create a better risk-return trade-off. Sharpe ratios range from 0.44 for the Quality Plus Low Volatility portfolio to 0.72 for the Momentum Plus Value portfolio in Panel A. More importantly, there is an impressive enhancement in the reported Information ratios, which means that by combining two or more strategies, an investor could generate higher active returns without increasing the tracking error significantly from the Benchmark. Now, looking at the $Sharpe_i/Sharpe_{BMK}$ ratio in Panel A, these strategies generate up to seven times the Benchmark's Sharpe ratio.

Consequently, by taking long positions in stocks with characteristics of two or more anomalies, an investor could significantly enhance the return per unit of risk of a passive strategy that invests in LatAm equity markets: each Sharpe ratio's t-value for the Jobson and Korkie test is exceptionally high. The difference to the Benchmark's Sharpe ratio is significant at the 1% level. When compared to the Benchmark and the Market Portfolio, there is also an improvement in the number of months with positive returns and the percentage of months each strategy beats the Benchmark is well above the 50% threshold. Diversification among strategies also helps to reduce the potential loss measured by the maximum drawdown. All combinations generate a lower maximum drawdown compared to both the Benchmark's and the Market portfolio's.

From all possible combinations, Momentum Plus Value, Value Plus Low Volatility, and the Multifactor portfolio are the most robust strategies reported in Table XXV measured by the Sharpe ratio. Panel B of Table XXV reports the same performance statistics as in Panel A but for multi-factor portfolios formed using a signal blending approach. The idea behind it is to determine whether the combination of strategies is better by using a portfolio blending approach or a signal blending approach. It is essential to mention here, too, that using the signal blending approach also creates an improvement in the ability of single-factor strategies to generate better returns per unit of risk. There is already a myriad of existing literature about the performance of both methodologies. Interestingly, results regarding the two approaches are mixed. For instance, Clarke, de Silva, and Thorley (2016) found that long-only multi-factor portfolios of individual securities (i.e., signal blending approach) attract most of the potential enhancement over the Market's Sharpe ratio; whereas Ghayur, Heaney, and Platt (2016) documented that for low-to-moderate factor levels, the portfolio blending approach generates better risk-adjusted returns.

Table XXV

Performance Statistics for Long-Only Multi-factor Portfolios formed using a Portfolio- and Signal-Blending Approach

This table reports the performance statistics for long-only multi-factor portfolios formed using a portfolio blending approach and a signal blending approach. Panel A shows the statistics on seven portfolios by equally combining Momentum, Value, Low Volatility, and Quality using a portfolio blending approach. Panel B shows the statistics on seven portfolios by combining Momentum, Value, Low Volatility, and Quality using a signal blending approach. The multifactor portfolio combines all strategies simultaneously. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The Benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio. Beta is the slope of the regression between the returns of each portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe Ratio of each portfolio and the Benchmark's Sharpe Ratio. The Information Ratio represents the active return concerning the Benchmark divided by its tracking error or standard deviation. The Sharpe Ratio represents the return per unit of risk. The $Sharpe_i/Sharpe_{BMK}$ ratio illustrates the improvement of portfolio i's Sharpe Ratio concerning the Benchmark's Sharpe Ratio. Max Drawdown represents the maximum loss from the peak to the bottom of the equity.

Panel A: Statistics for Multi-factor Portfolios using the Portfolio Blending Approach

	Quality + Low Vol	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Vol	Value + Low Vol	Multifactor	BMK	RMRF
Excess Returns (%)	6.89	12.53	10.78	14.47	8.74	10.46	10.62	2.80	10.94
Standard Deviation (%)	15.55	20.91	21.02	20.12	15.47	14.84	17.36	26.97	25.38
Max (%)	10.47	17.64	16.70	14.49	13.98	11.13	11.72	18.54	22.19
Min (%)	-26.46	-32.34	-32.78	-30.42	-24.54	-24.10	-28.44	-38.36	-35.62
Beta	0.49	0.68	0.70	0.65	0.46	0.44	0.57	0.94	1.00
Sharpe Ratio	0.44	0.60	0.51	0.72	0.56	0.70	0.61	0.10	0.43
T-Value	7.47	10.76	9.64	12.30	8.81	10.90	11.09	0.00	21.35
$Sharpe_i/Sharpe_{BMK}$	4.26	5.77	4.93	6.92	5.43	6.78	5.89	1.00	4.15
Information Ratio	0.25	0.72	0.59	0.82	0.33	0.43	0.53		0.62
% Positive Months	59.21	60.53	61.84	61.40	59.21	60.53	61.84	55.26	57.02
% Months beats BMK	55.26	59.21	59.21	62.28	57.46	55.26	57.89		58.33
Max Drawdown (%)	-49.04	-59.98	-59.80	-57.27	-46.97	-45.91	-53.17	-76.57	-62.82

Panel B: Statistics for Multi-factor Portfolios using the Signal Blending Approach

	Quality + Low Vol	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Vol	Value + Low Vol	Multifactor	BMK	RMRF
Excess Returns (%)	8.30	9.57	10.20	12.68	8.51	10.31	11.30	2.80	10.94
Standard Deviation (%)	20.00	21.63	20.74	19.41	16.40	13.45	19.56	26.97	25.38
Max (%)	17.99	19.44	17.27	14.00	12.27	11.39	18.33	18.54	22.19
Min (%)	-33.76	-34.10	-33.50	-28.00	-21.62	-19.02	-35.00	-38.36	-35.62
Beta	0.64	0.70	0.67	0.59	0.40	0.35	0.61	0.94	1.00
Sharpe Ratio	0.42	0.44	0.49	0.65	0.52	0.77	0.58	0.10	0.43
T-Value	7.12	7.80	8.88	10.43	6.76	10.51	9.64	0.00	21.35
$Sharpe_i/Sharpe_{BMK}$	3.99	4.26	4.73	6.29	4.99	7.37	5.56	1.00	4.15
Information Ratio	0.38	0.49	0.53	0.61	0.28	0.37	0.58		0.62
% Positive Months	60.96	60.09	60.53	58.33	57.02	58.33	60.96	55.26	57.02
% Months beats BMK	55.70	55.70	56.14	58.33	57.02	57.46	57.89		58.33
Max Drawdown (%)	-60.13	-60.88	-58.72	-52.79	-44.99	-38.70	-58.48	-76.57	-62.82

Results reported in Table XXV are mixed regarding the implementation of a portfolio blending approach or a signal blending approach. It depends on what measures are used to compare the efficiency in blending strategies. Sharpe ratios do not differ much from one approach to another, but they tend to be higher for multi-factor portfolios in Panel A. However, when considering Information Ratios a signal blending approach could be better used especially if an investor desires to reunite all strategies at once. Nevertheless, results in Table XXV favor the use of a portfolio blending approach by taking into account other performance metrics such as Maximum Drawdown. As we want to reduce the potential loss in any strategy, a portfolio blending approach reduces the most significant loss vastly compared to portfolios formed in Panel B. Hence, our results are more in line to those reported by Ghayur, Heaney, and Platt (2016). Anyhow, the difference in performance between the two methodologies is not material, and both generate better results compared to the Benchmark and the Market portfolio. Thus, the implementation of one approach or the other would depend on the investor's specific investment objectives such as the reduction in turnover and transaction costs which favors a signal blending approach or the increase in Sharpe ratio which benefits the portfolio blending approach. Anyhow, Table XXV helps to reject Hypothesis 4 that states that a signal blending approach is a better approximation when creating multi-factor strategies as documented by most academic literature.

6.4 A dynamic asset allocation strategy for multi-factor portfolios

In this section, we continue leveraging our understanding of Momentum to create an asset allocation strategy to active portfolio positioning. To reinforce the idea behind Momentum, we present a simple Absolute Momentum strategy on the MSCI Emerging Markets Latin American Index (MXLA). The strategy goes long multi-factor portfolios, which have been proved to generate abnormal excess returns with respect to the Benchmark, when the cumulative returns of the past 12 months (inclusive) of the MXLA is positive and goes long the Barclays U.S. Aggregate Bond Index when the cumulative returns of the past 12 months (inclusive) of the MXLA is negative. The signal is generated at the end of each month and holds throughout the next month. For instance, if at the 31st of January 2000 the cumulative Momentum return is positive for the MXLA, then February 2000 would be a month to be long in multi-factor portfolios. This simple strategy seeks to retain the upside potential in bull markets while going cautious during bear markets.

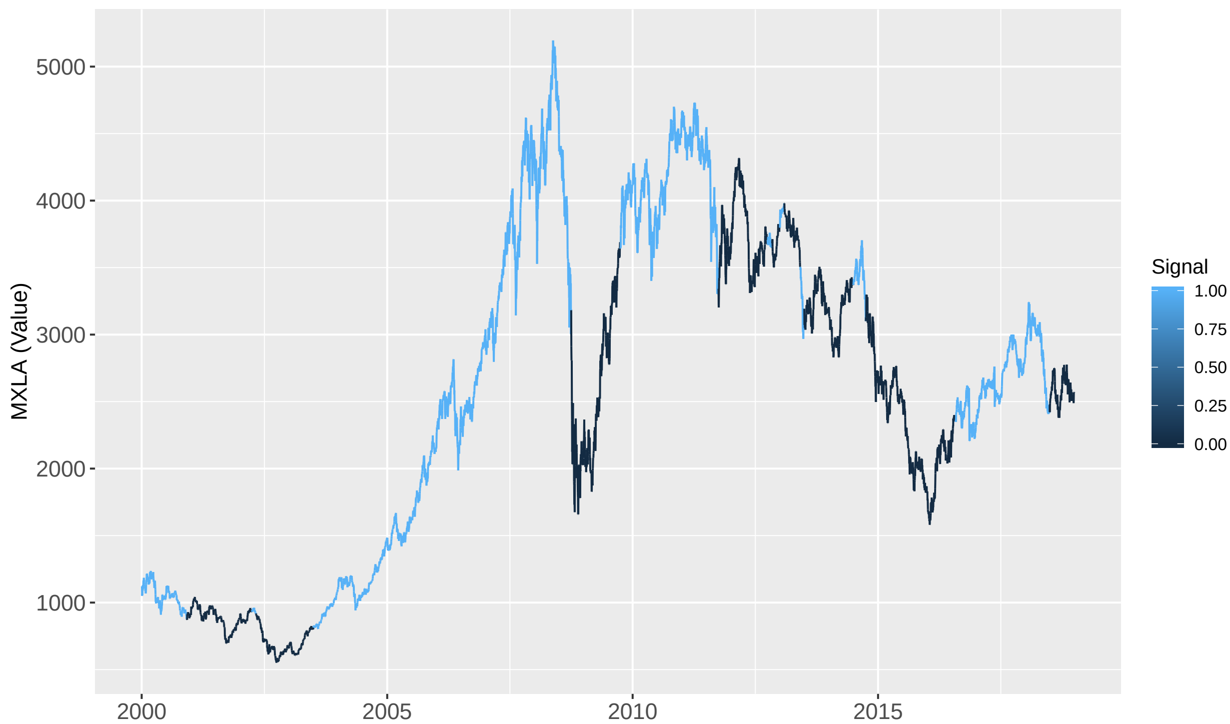

Figure 6
MSCI Emerging Markets Latin America Index with an Absolute Momentum signal. This Figure shows the historical evolution of the MSCI Emerging Markets Latin America Index with an active asset allocation strategy signal overlayed on top as a color gradient from January 2000 to December 2018. Light blue means that the strategy favors being long multi-factor portfolios and dark blue means that the strategy benefits being long the Barclays U.S. Aggregate Bond Index.

Figure 6 shows the daily closing price for the MSCI Emerging Markets Latin America Index from the 1st of January 2000 to the 31st of December 2018 with the trading signal overlayed on top as a color gradient. Light blue means that the strategy favors being long multi-factor portfolios (the signal is +1) and dark blue means that the strategy benefits being long the Barclays U.S. Aggregate Bond Index (the signal is 0). The strategy helps to avoid sharp downturns in equity markets and look for safety in fixed income markets. Figure 6 shows that the use of Absolute Momentum as a dynamic asset allocation strategy has been a useful risk management tool to stay in the sidelines in periods of market turbulence while allowing to hold multi-factor portfolios in risk-on scenarios. However, it is essential to highlight that in substantial market recoveries the implementation of Absolute Momentum as a factor timing tool may stay behind as it happened after the 2008 financial crisis leading to a loss of confidence in the strategy. Nevertheless, for the last couple of years and during the collapse of commodity prices, this approach would have helped to avoid a significant drawdown.

Figure 7
Sharpe ratio enhancement by implementing a dynamic asset allocation strategy. This Figure shows the improvement of implementing a dynamic asset allocation strategy using an Absolute Momentum signal into multi-factor portfolios' Sharpe ratios. The pink bars represent the Sharpe ratio for each portfolio after implementing a Dynamic A.A. strategy, and the blue bars represent the Sharpe ratio for every multi-factor portfolio. The Sharpe ratios are generated using return data from January 2000 to December 2018.

Figure 7 illustrates more clearly the benefits of using Absolute Momentum as a dynamic asset allocation strategy. This graph plots the Sharpe ratios for all multi-factor portfolios considered in sections 6.3.1 and 6.3.2 and the Sharpe ratios when a dynamic asset allocation is employed simultaneously. For all multi-factor strategies, there is a considerable improvement in the Sharpe ratio. The risk-return trade-off increases dramatically above the one threshold in most cases. The most significant enhancement is seen for the Quality plus Low Volatility portfolio: its Sharpe ratio increases from 0.44 when combining only these two effects to 1.03 when the multi-factor portfolio is actively managed with the Barclays U.S. Aggregate Bond Index. Figure 8 also highlights that a dynamic asset allocation strategy corrects two of the most undesired properties of stock returns: fat tails and negative skewness. This shape plots the monthly returns' distribution of multi-factor portfolios with a dynamic asset allocation strategy. The pink area represents the monthly returns' distribution for the MSCI Emerging Markets Latin America Index.

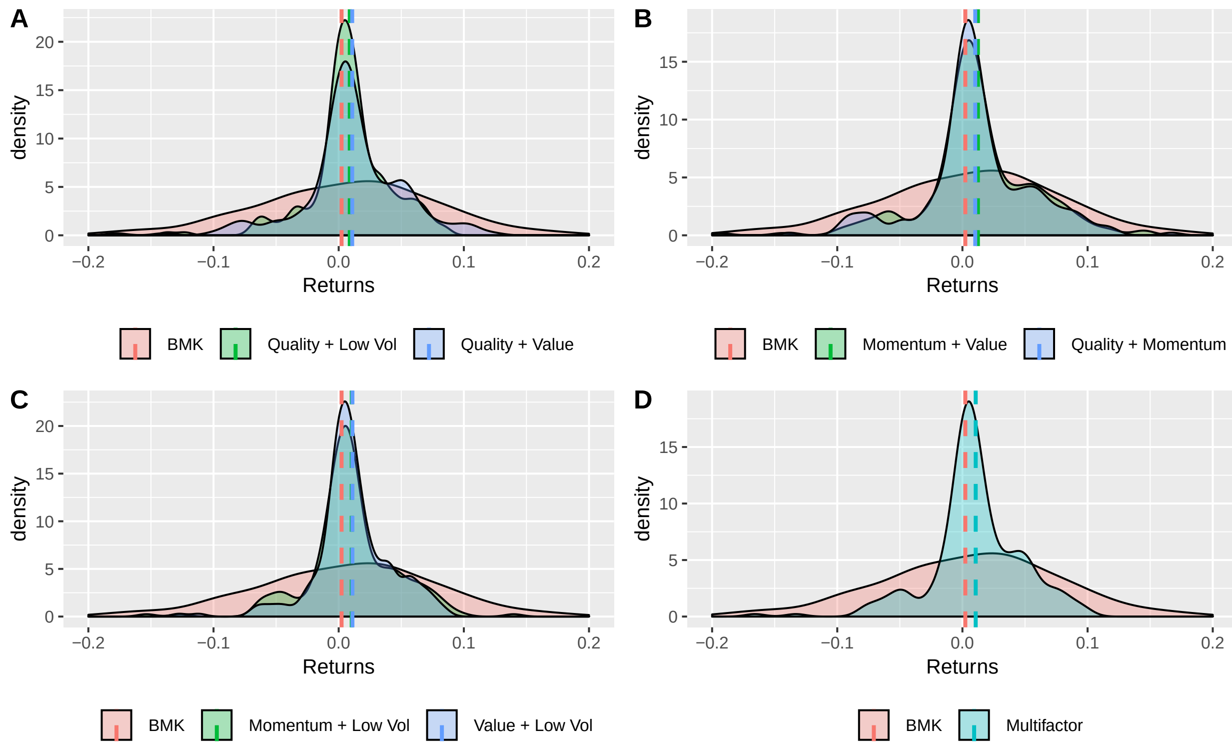

Figure 8
Returns' distribution of multi-factor portfolios with a dynamic asset allocation strategy. This Figure shows the improvement of implementing a dynamic asset allocation strategy using an Absolute Momentum signal into multi-factor portfolios' returns distribution. The pink area represents the monthly returns' distribution for the Benchmark, and the colored areas represent the monthly returns' distribution for each multi-factor portfolio after implementing a dynamic asset allocation strategy. The vertical line represents the median value for each return distribution. The returns' distributions are generated using return data from January 2000 to December 2018.

The blue- and green-colored areas represent the monthly returns' distribution for each multi-factor portfolio after implementing a dynamic asset allocation strategy. For the Benchmark (i.e., the pink-colored area), returns tend to be widely spread, with many occurrences at the tails of the distribution. It means that extraordinarily negative or positive monthly returns are not as rare as an investor may think. Contrarily, the returns' distribution for the blue- and green-colored areas are concentrated close to the mean. Applying a dynamic asset allocation strategy to multi-factor portfolios reduces the exposure to extremely adverse events and makes the distribution to be positively skewed: there are more returns occurrences above the zero level. Furthermore, for all multi-factor portfolios depicted in Figure 7, the average monthly return is always above the Benchmark's. Table XXVI displays the performance statistics of multi-factor portfolios after executing a dynamic asset allocation. It supports conclusions drawn from Figures 7 and 8 for all multi-factor portfolios: the expected average monthly return is increased, and the expected standard deviation is cut at half is some cases.

Table XXVI

Performance Statistics for Multi-factor Portfolios using a Dynamic Asset Allocation Strategy

This table reports the performance statistics for multi-factor portfolios after implementing a dynamic asset allocation strategy and shows the statistics on seven portfolios by equally combining Momentum, Value, Low Volatility, and Quality using a portfolio blending approach. The multifactor portfolio combines simultaneously all strategies. RMRF represents the value-weighted return of all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. The benchmark represents the return of the MSCI Emerging Markets Latin America Index. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio. Beta is the slope of the regression between the returns of each portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe Ratio of each portfolio and the Benchmark's Sharpe Ratio. The Information Ratio represents the active return with respect to the Benchmark divided by its tracking error or standard deviation. The Sharpe Ratio represents the return per unit of risk. The $Sharpe_i/Sharpe_{BMK}$ ratio illustrates the improvement of portfolio i's Sharpe Ratio with respect to the Benchmark's Sharpe Ratio. The Max Drawdown represents the maximum loss from the peak to the bottom of the equity.

	Quality + Low Vol	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Vol	Value + Low Vol	Multifactor	BMK	RMRF
Excess Returns (%)	11.15	13.74	13.01	15.90	13.26	14.00	13.50	2.80	10.94
Standard Deviation (%)	10.87	14.09	15.91	15.41	12.24	10.49	12.75	26.97	25.38
Max (%)	8.57	12.39	16.70	14.48	13.98	8.47	10.04	18.54	22.19
Min (%)	-13.71	-17.79	-21.96	-19.42	-15.35	-12.78	-16.57	-38.36	-35.62
Beta	0.20	0.27	0.32	0.31	0.24	0.19	0.25	0.94	1.00
Sharpe Ratio	1.03	0.98	0.82	1.03	1.08	1.33	1.06	0.10	0.43
T-Value	11.35	11.01	9.64	11.61	11.96	13.48	11.88		21.35
$Sharpe_i/Sharpe_{BMK}$	10.30	9.80	8.20	10.30	10.80	13.30	10.60	1.00	4.30
Information Ratio	0.35	0.47	0.45	0.57	0.45	0.47	0.47		0.62
% Positive Months	69.30	69.74	68.86	68.86	67.98	71.05	70.18	55.26	57.02
% Months beats BMK	56.58	58.33	57.02	59.21	57.46	56.58	57.46		58.33
Max Drawdown (%)	-26.60	-34.10	-36.30	-34.00	-26.08	-23.84	-30.18	-76.57	-62.82

More importantly, the minimum monthly return and the maximum drawdown are reduced significantly. This fact highlights the implementation of Absolute Momentum as a capital preserving strategy in the long-term. The number of months with positive returns is improved close to a 70% and, surprisingly, the beta for each multi-factor portfolio concerning the Benchmark is now closer to zero. All in all, Figures 7 and 8 plus Table XXVI serve as empirical evidence regarding Hypothesis 5 which states that Absolute Momentum can successfully be used as a factor timing to improve the return per unit of risk of multi-factor portfolios.

7 Robustness Checks

In this section, we perform a variety of tests to look at the strategies reported so far from different points of view so we can get a better understanding of the properties for each of them. We first analyze all strategies at different time intervals from January 2000 to December 2018. We then show the results of quintile portfolios instead of decile portfolios. Later on, we illustrate the performance statistics of value-weighted decile portfolios as an alternative of equally-weighted portfolios. Then, we document the alphas generated for each long-only multi-factor portfolio when the portfolios' excess returns are regressed against the asset pricing models and, finally, we shows the effects of liquidity constraints on systematic risk factors.

7.1 Performance by cycle, 2000-2018

In the previous sections, we have reported the performance statistics for all strategies for the whole sample period ranging from January 2000 to December 2018. However, as shown by Tables XXXIX and XXXX, many strategies may have long periods of underperformance eroding the confidence an investor has over a specific strategy. Therefore, we report the performance statistics of all strategies considered so far in this research in different regimes. We focus ourselves in the most influential anomaly definitions reported in Section 6.2. It allows assessing not only the cyclicity some strategies have according to the business cycle and the mood of the market (i.e., bullish or bearish) but also which ones are the strongest at any market cycle.

We divide the whole sample period into three-time intervals: From January 2000 to December 2006, from January 2007 to December 2013, and from January 2014 to December 2018. These periods coincide with important market events and business cycles in LatAm. The first period concurs with the tech-bubble burst in the US and the default of Argentina's sovereign debt. The second period includes the Global Financial Crisis and the start of the Quantitative Easing (QE) programs implemented by major Central Banks. The last cycle concurs with the decline in commodities prices, the strength of the dollar, and the economic downturn in most LatAm economies. Table XXVII shows the performance statistics for single-factor portfolios, Table XXVIII depicts the performance statistics for multi-factor portfolios, and Table XXIX exhibits the performance statistics when a dynamic asset allocation is applied to multi-factor portfolios.

Table XXVII shows that single-factor portfolios may pose long periods of underperformance compared to both the Benchmark and the Market portfolio. For instance, the 2000-2006 bullish period was particularly weak for the Low Volatility anomaly. When considering a long/short strategy, the performance is negative as short positions lag long positions. Contrarily, in the 2014-2018 bearish time interval, the Low Volatility effect proves to be a successful strategy. All other difference portfolios generate annual excess returns and Sharpe ratios higher than the Benchmark and the Market portfolio. The Quality effect tends to be weak in specific business cycles, while the Momentum and the Value anomaly are the strongest. However, as short positions are challenging to hold in the long-term, long-only portfolios would be a more realistic scenario for most investors with short-sell restrictions. The 2014-2018 cycle is the most challenging for most strategies. Despite almost all strategies beat the Benchmark, none of them beat the Market portfolio in this period. Five years of underperformance may defy the trust over any investment strategy. Consequently, the combination of different strategies may help to solve this problem.

Table XXVIII shows that the combination of two or more strategies improves the performance of single-factor portfolios across the business cycles. Sharpe ratios are particularly enhanced for the first two time intervals studied. It means that all strategies in all periods reduce the annual standard deviation significantly compared to single-factor portfolios. However, the creation of multi-factor portfolios does not exempt periods of lousy performance. The 2014-2018 business cycle continues to be a challenge even for well-diversified multi-factor portfolios. All strategies earn higher annual excess returns over the Benchmark, but none of them beat the Market portfolio. Finally, Table XXIX exhibits the improvement desired in the last business cycle when a dynamic asset allocation strategy is applied to multi-factor portfolios. Although some strategies do not generate the same or higher annual excess return than the Market portfolio, all strategies earn the same or even a higher Sharpe ratio compared to both the Benchmark and the Market portfolio.

Table XXVII

Performance Statistics for Single-Factor Portfolios in Multiple Time Intervals, 2000-2018

This table reports the performance statistics on four different strategies and four time intervals. The strategies are Momentum, Value, Low Volatility, and Quality. The first time interval covers the whole data, the second time interval spans from January 2000 to December 2006, the third comprises returns from January 2007 to December 2013, and finally, the period from January 2014 to December 2018 is fully covered. Panel A shows the average returns, the annual standard deviation, the annual Sharpe ratio, and the maximum drawdown for the difference portfolio. Panel B shows the performance statistics for top decile portfolios. Finally, Panel C illustrates the performance statistics for the Benchmark (i.e., the MSCI Emerging Markets Latin America Index) and the Market portfolio (i.e., RMRF).

	Panel A: Difference Portfolio				**Panel B: Top Decile Portfolio**				**Panel C**	
	Momentum	Value	Low Volatility	Quality	Momentum	Value	Low Volatility	Quality	Benchmark	RMRF
All Data										
Annual Returns	20.62%	19.72%	8.04%	9.25%	12.69%	16.27%	4.91%	8.90%	2.80%	10.68%
Annual Std Deviation	20.99%	14.44%	29.31%	13.12%	21.96%	20.71%	12.65%	22.13%	26.97%	25.31%
Annual Sharpe	0.98	1.37	0.27	0.71	0.58	0.79	0.39	0.40	0.10	0.42
Max Drawdown	-54.48%	-25.97%	-87.47%	-34.54%	-58.37%	-62.21%	-46.36%	-62.35%	-76.57%	-62.19%
2000-2006										
Annual Returns	15.81%	21.62%	-7.85%	12.47%	25.18%	30.87%	5.53%	23.35%	11.62%	13.17%
Annual Std Deviation	19.23%	15.24%	30.10%	13.62%	22.57%	16.38%	12.91%	22.22%	26.24%	28.87%
Annual Sharpe	0.82	1.42	-0.26	0.92	1.12	1.88	0.43	1.05	0.44	0.46
Max Drawdown	-34.25%	-25.97%	-84.77%	-27.66%	-42.94%	-24.35%	-46.36%	-50.37%	-61.95%	-62.19%
2007-2013										
Annual Returns	20.45%	25.72%	19.06%	4.81%	8.76%	15.00%	9.56%	6.32%	0.03%	10.23%
Annual Std Deviation	21.38%	14.53%	30.17%	11.46%	24.33%	25.82%	14.44%	24.91%	29.52%	25.87%
Annual Sharpe	0.96	1.77	0.63	0.42	0.36	0.58	0.66	0.25	0.00	0.40
Max Drawdown	-54.48%	-11.41%	-65.45%	-34.54%	-58.37%	-56.32%	-34.42%	-62.35%	-67.29%	-57.66%
2014-2018										
Annual Returns	27.93%	9.33%	17.57%	11.16%	2.10%	-0.12%	-2.12%	-5.58%	-4.87%	7.90%
Annual Std Deviation	22.94%	12.99%	26.50%	14.60%	16.84%	17.24%	9.04%	16.73%	24.28%	18.71%
Annual Sharpe	1.22	0.72	0.66	0.76	0.12	-0.01	-0.23	-0.33	-0.20	0.42
Max Drawdown	-39.95%	-25.12%	-51.51%	-21.67%	-36.26%	-49.37%	-24.89%	-45.39%	-54.78%	-32.94%

Table XXVIII

Performance Statistics for Multi-Factor Portfolios in Multiple Time Intervals, 2000-2018

This table reports the performance statistics on seven multi-factor strategies in four time intervals. The equally-weighted multi-factor strategies are built based on Momentum, Value, Low Volatility, and Quality. The multifactor portfolios invest equally in all strategies just mentioned. The first time interval covers the whole data, the second time interval spans from January 2000 to December 2006, the third comprises returns from January 2007 to December 2013, and finally, the period from January 2014 to December 2018 is fully covered. Panel A shows the average returns, the annual standard deviation, the annual Sharpe ratio, and the maximum drawdown for all the multi-factor portfolios. Panel B illustrates the performance statistics for the Benchmark (i.e., the MSCI Emerging Markets Latin America Index) and the Market portfolio (i.e., RMRF).

	Panel A: Multi-Factor Portfolios							**Panel B**	
	Quality + Low Volatility	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Volatility	Value + Low Volatility	Multifactor	Benchmark	RMRF
All Data									
Annual Returns	6.89%	12.53%	10.78%	14.47%	8.74%	10.46%	10.62%	2.80%	10.68%
Annual Std Deviation	15.55%	20.91%	21.02%	20.12%	15.47%	14.84%	17.36%	26.97%	25.31%
Annual Sharpe	0.44	0.60	0.51	0.72	0.56	0.70	0.61	0.10	0.42
Max Drawdown	-49.04%	-59.98%	-59.80%	-57.27%	-46.97%	-45.91%	-53.17%	-76.57%	-62.19%
2000-2006									
Annual Returns	14.11%	27.05%	24.26%	27.99%	14.97%	17.57%	20.87%	11.62%	13.17%
Annual Std Deviation	14.48%	18.74%	21.37%	18.18%	14.37%	11.81%	15.61%	26.24%	28.87%
Annual Sharpe	0.97	1.44	1.14	1.54	1.04	1.49	1.34	0.44	0.46
Max Drawdown	-37.38%	-34.47%	-45.82%	-29.88%	-32.94%	-23.27%	-31.34%	-61.95%	-62.19%
2007-2013									
Annual Returns	7.94%	10.59%	7.54%	11.84%	9.17%	12.26%	9.87%	0.03%	10.23%
Annual Std Deviation	18.33%	24.99%	23.67%	23.96%	18.34%	18.56%	20.81%	29.52%	25.87%
Annual Sharpe	0.43	0.42	0.32	0.49	0.50	0.66	0.47	0.00	0.40
Max Drawdown	-49.04%	-58.80%	-59.80%	-57,27%	-46.97%	-45.91%	-53.17%	-67.29%	-57.66%
2014-2018									
Annual Returns	-3.86%	-2.88%	-1.81%	0.98%	-0.03%	-1.12%	-1.47%	-4.87%	7.90%
Annual Std Deviation	12.17%	16.50%	15.48%	15.99%	12.16%	12.29%	13.63%	24.28%	18.71%
Annual Sharpe	-0.32	-0.17	-0.12	0.06	-0.00	-0.09	-0.11	-0.20	0.42
Max Drawdown	-35.12%	-47.39%	-40.90%	-43.06%	-29.97%	-37.49%	-39.19%	-54.78%	-32.94%

Table XXIX

Performance Statistics for a Dynamic Asset Allocation Strategy in Multiple Time Intervals, 2000-2018

This table reports the performance statistics when a dynamic asset allocation strategy is applied to seven multi-factor portfolios in four time intervals. The equally-weighted multi-factor strategies are built based on Momentum, Value, Low Volatility, and Quality. The multifactor portfolios invest equally in all strategies just mentioned. The first time interval covers the whole data, the second time interval spans from January 2000 to December 2006, the third comprises returns from January 2007 to December 2013, and finally, the period from January 2014 to December 2018 is fully covered. Panel A shows the average returns, the annual standard deviation, the annual Sharpe ratio, and the maximum drawdown for all the multi-factor portfolios. Panel B illustrates the performance statistics for the Benchmark (i.e., the MSCI Emerging Markets Latin America Index) and the Market portfolio (i.e., RMRF).

	Panel A: Dynamic Asset Allocation Strategy							**Panel B**	
	Quality + Low Volatility	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Volatility	Value + Low Volatility	Multifactor	Benchmark	RMRF
All Data									
Annual Returns	11.15%	13.74%	13.01%	15.90%	13.26%	14.00%	13.50%	2.80%	10.68%
Annual Std Deviation	10.87%	14.09%	15.91%	15.41%	12.24%	10.49%	12.75%	26.97%	25.31%
Annual Sharpe	1.03	0.98	0.82	1.03	1.08	1.33	1.06	0.10	0.42
Max Drawdown	-26.60%	-34.10%	-36.30%	-34.00%	-26.08%	-23.84%	-30.18%	-76.57%	-62.19%
2000-2006									
Annual Returns	19.97%	26.37%	25.71%	27.50%	21.05%	21.69%	23.69%	11.62%	13.17%
Annual Std Deviation	10.57%	13.33%	17.02%	15.02%	12.17%	8.92%	12.30%	26.24%	28.87%
Annual Sharpe	1.89	1.98	1.51	1.83	1.73	2.43	1.93	0.44	0.46
Max Drawdown	-17.91%	-15.93%	-25.33%	-18.21%	-17.07%	-10.58%	-16.25%	-61.95%	-62.19%
2007-2013									
Annual Returns	8.44%	9.30%	7.41%	10.94%	10.07%	12.00%	9.68%	0.03%	10.23%
Annual Std Deviation	12.82%	17.08%	17.45%	18.10%	14.10%	13.46%	15.15%	29.52%	25.87%
Annual Sharpe	0.66	0.54	0.42	0.60	0.71	0.89	0.64	0.00	0.40
Max Drawdown	-26.60%	-34.10%	-36.30%	-34.00%	-26.08%	-23.84%	-30.18%	-67.29%	-57.66%
2014-2018									
Annual Returns	3.34%	3.67%	4.42%	7.72%	7.37%	6.61%	5.51%	-4.87%	7.90%
Annual Std Deviation	7.35%	8.97%	10.76%	10.86%	8.89%	6.89%	8.67%	24.28%	18.71%
Annual Sharpe	0.45	0.41	0.41	0.71	0.83	0.96	0.64	-0.20	0.42
Max Drawdown	-15.83%	-17.69%	-20.78%	-14.59%	-12.66%	-9.33%	-15.20%	-54.78%	-32.94%

In all strategies, the standard deviation is reduced in half, and the Sharpe ratio achieves an extraordinary value close to or above the 2 level threshold in some cycles (i.e., 2.43 for the Value Plus Low Volatility strategy in the 2000-2006 period). Therefore, we could argue that effectively selecting between multi-factor portfolios and fixed income securities through a dynamic asset allocation strategy is the best alternative to invest in LatAm equity markets at any business cycle

7.2 Quintile portfolios

We assess single-factor and multi-factor portfolios using quintiles instead of deciles. As portfolios are more diversified when using quintiles, we could expect a reduction in the performance statistics of quintile portfolios versus decile portfolios. However, as a robustness check, results may not differ significantly, and the anomalies should be still present no matter how portfolios are formed. Table XXX shows the average descriptive statistics for quintile portfolios formed on Momentum, Value, Low Volatility, and Quality. In Section 6.2, various definitions for each anomaly were tested, creating ten decile portfolios. Table XXX takes the average of the descriptive statistics for the same anomalies definitions in each category but creating five different quintile portfolios instead. For instance, Panel A takes the average excess return on Momentum portfolios sorted on $r_{12,1}$, $r_{12,7}$, $r_{6,2}$, and Quality Momentum $r_{12,1}$ over five different quintile portfolios. Each panel also reports the alphas generated after controlling for systematic risk factors for the CAPM Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model.

In general, all anomalies are still present even after forming five quintile portfolios. Excess returns increase from Q1 to Q5 in all Panels, and the reported alphas are statistically different from zero and positive for the difference portfolios. Thus, taking long positions in stocks with favored characteristics and selling-short stocks simultaneously with undesired characteristics can generate abnormal excess returns that cannot be explained by any asset pricing model. Therefore, results are robust even after forming five quintile portfolios. However, the magnitude of the excess returns in the difference portfolio is reduced significantly. For instance, the average excess return for the difference portfolios in the four Momentum strategies described in Table VI is close to 16.25% versus the 11.76% excess return reported in Table XXX Panel A for the same four Momentum strategies. For the other three anomalies, the reduction is also evident: It reduces from 16.25% to 11.43% for Value, from 9% to 6.23% for Low Volatility, and from 9.5% to 8.21% for Quality.

Table XXX

Descriptive Statistics for Quintile Portfolios

This table reports the descriptive statistics for 20 quintile portfolios sorted on Momentum, Value, Low Volatility, and Quality. LATAM breakpoints are used when sorting on each strategy. Q1 contains stocks with undesired characteristics, whereas Q5 contains stocks with desired characteristics. Q5-1 represents the difference portfolio for each category. For every Panel, all descriptive statistics correspond to the average of all anomaly definitions reported in Section 5.3 for each strategy. All figures are calculated on an annual basis except maximums, minimums, the Beta, and the Information Ratio (IR). Beta is the slope of the regression between the returns of each decile portfolio as a function of the RMRF. T-value represents the t-statistic for the Jobson and Korkie test for the difference between the Sharpe ratio of each quintile portfolio and the RMRF's Sharpe ratio. The Alphas reported correspond to the excess returns after controlling for systematic risk factors for the CAPM Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model. The data sample for this strategy contains 614 unique companies between 2000 and 2018.

	Panel A: Momentum						Panel B: Value					
	Q1	Q2	Q3	Q4	Q5	Q5-1	Q1	Q2	Q3	Q4	Q5	Q5-1
Excess Return	-2.51%	4.78%	6.88%	7.83%	8.97%	11.76%	-1.10%	3.75%	3.18%	6.07%	10.14%	11.43%
Volatility	28.06%	22.38%	19.59%	18.86%	21.48%	18.47%	23.82%	21.88%	19.40%	18.97%	19.98%	11.75%
Max	27.78%	20.63%	16.13%	14.14%	14.43%	13.20%	18.55%	20.88%	16.16%	15.91%	18.19%	16.13%
Min	-43.70%	-37.31%	-32.95%	-28.45%	-35.17%	-20.97%	-38.99%	-35.62%	-32.50%	-32.03%	-29.32%	-10.85%
Beta	0.91	0.74	0.66	0.63	0.69	-0.22	0.79	0.75	0.64	0.64	0.65	-0.14
Sharpe Ratio	-0.09	0.21	0.35	0.42	0.42	0.64	-0.04	0.17	0.17	0.32	0.51	0.98
T-Value	-4.72	2.84	6.56	7.70	7.16	4.83	-3.61	0.97	1.31	4.75	8.24	6.95
IR	-0.36	0.16	0.32	0.38	0.43	0.23	-0.29	0.06	0.03	0.25	0.55	0.26
CAPM (Alpha)	-3.15***	-0.99	-0.05	0.49	0.57	3.30***	-2.96**	-1.56	-1.33	-0.27	1.16	4.83**
Fama French (Alpha)	-5.44***	-3.31***	-2.74***	-2.14**	-2.39**	3.01***	-5.38***	-4.14***	-3.94***	-2.90***	-1.24	4.59**
Carhart (Alpha)	-4.65***	-2.38**	-2.19**	-2.38**	-3.49***	1.74	-5.01***	-3.75***	-3.33***	-2.32**	-0.84	4.51**

	Panel C: Low Volatility						Panel D: Quality					
	Q1	Q2	Q3	Q4	Q5	Q5-1	Q1	Q2	Q3	Q4	Q5	Q5-1
Excess Return	0.09%	6.24%	5.29%	6.92%	6.33%	6.23%	0.36%	2.54%	6.30%	6.18%	8.60%	8.21%
Volatility	32.86%	25.60%	20.02%	16.75%	12.97%	25.60%	24.07%	21.60%	20.36%	19.18%	18.75%	13.34%
Max	28.40%	20.81%	16.48%	13.00%	11.61%	29.19%	17.22%	17.67%	17.38%	15.28%	16.66%	15.30%
Min	-48.88%	-40.03%	-37.10%	-28.90%	-19.69%	-22.04%	-34.98%	-34.54%	-35.86%	-32.39%	-30.34%	-14.87%
Beta	1.10	0.89	0.68	0.53	0.34	-0.76	0.80	0.74	0.69	0.65	0.61	-0.19
Sharpe Ratio	0.00	0.24	0.27	0.41	0.49	0.24	0.02	0.12	0.31	0.32	0.48	0.67
T-Value	-2.76	4.14	4.40	6.96	6.75	1.13	-2.34	0.41	5.52	5.95	8.33	5.39
IR	-0.19	0.35	0.19	0.26	0.17	0.07	-0.19	-0.02	0.27	0.26	0.42	0.16
CAPM (Alpha)	-2.78***	-1.04	-0.71	0.57	1.21	3.53***	-2.55**	-1.98**	-0.36	-0.28	0.90	3.67***
Fama French (Alpha)	-5.64***	-4.06***	-3.70***	-2.07**	-1.09	4.57***	-5.77***	-4.80***	-3.32***	-2.79***	-1.36	4.34***
Carhart (Alpha)	-5.02***	-3.52***	-3.20***	-1.70	-0.91	4.02***	-5.32***	-4.27***	-2.78***	-2.28**	-1.05	4.13***

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Furthermore, long-only quintile portfolios are not as strong in terms of performance compared to long-only decile portfolios. Thus, the generated alphas after controlling for systematic risk factors are not significantly different from zero. Top quintile portfolios' alphas are not statistically significant even at the 10% level. Consequently, long-only top quintile portfolios may not generate abnormal excess returns after all as the portfolios are less tilted to the factors. We also want to report how the performance of multi-factor portfolios is affected if, instead of top decile portfolios, top quintile portfolios were chosen. Figure 9 reports the difference in Sharpe ratio generation when top quintile and top decile portfolios are selected to createlong-only multi-factor portfolios.

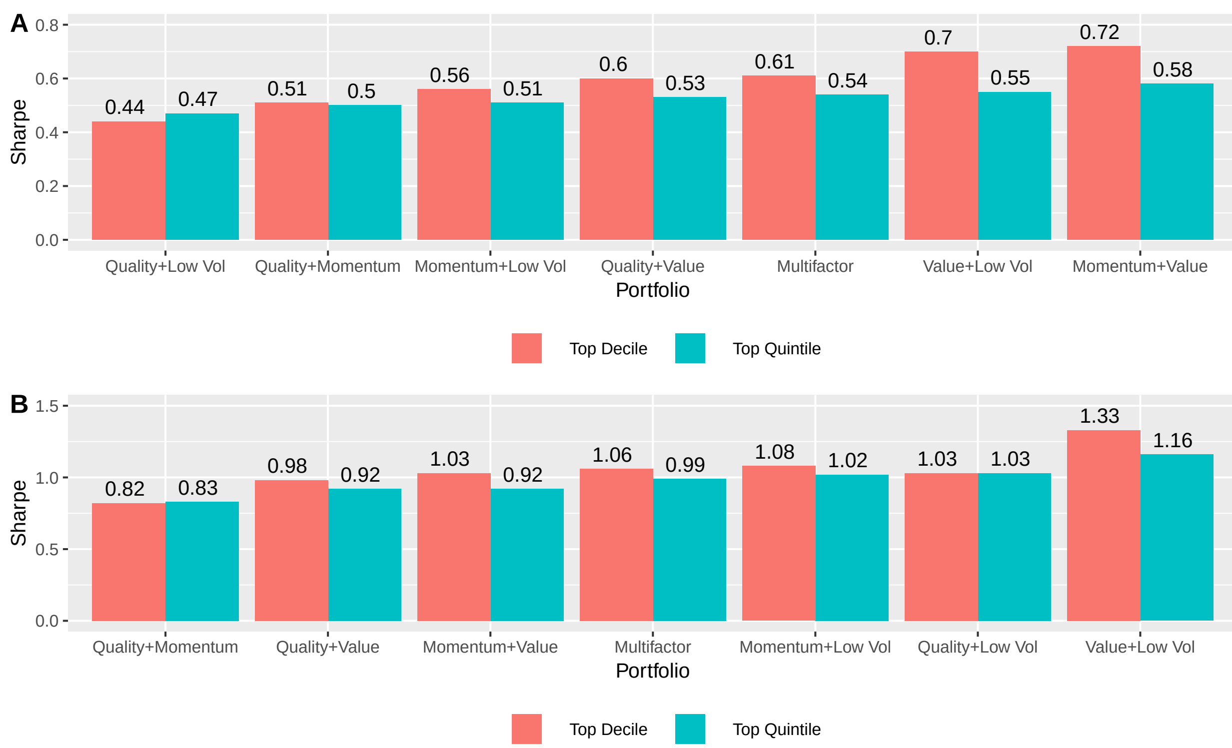

Figure 9
Top decile vs top quintile Sharpe ratios for multi-factor portfolios. This figure compares the Sharpe ratios for multi-factor portfolios when the combining strategies take into account the top decile portfolios and the top quintile portfolios. Panel A shows the Sharpe ratio generation for multi-factor portfolios only, while Panel B reports the Sharpe ratio generation when a dynamic asset allocation is applied to multi-factor portfolios. The Sharpe ratios are generated using return data from January 2000 to December 2018.

Panel A illustrates the Sharpe ratios for multi-factor portfolios only, and Panel B depicts Sharpe ratios when a dynamic asset allocation strategy is applied to multi-factor portfolios. On the overall, there exists still an improvement in Sharpe ratios when two or more strategies are put together after using top quintiles. Blue bars' values in Figure 9 are higher than those reported in Table XXX. However, when comparing the performance between top decile and top quintile portfolios, there is not a dramatic change. Almost all strategies generate equally Sharpe ratios, no matter whether the top quintile or decile portfolio is chosen. Significant differences can be seen when multi-factor portfolios are built without using a dynamic asset allocation strategy. For instance, the Sharpe ratio is reduced from 0.72 to 0.58 in the Momentum Plus Value strategy, and from 0.70 to 0.55 in the Value Plus Low Volatility strategy. Results in Panel B are more consistent than in Panel A, and there is no much difference whether the top decile or top quintile portfolios are selected. However, it is crucial mentioning here that performance reported so far are free of transaction costs. Therefore, Quintile portfolios may be prone to higher transaction costs and, thus, lower expected returns and Sharpe ratios.

7.3 Value-weighted portfolios

We evaluate single-factor portfolios by using a value-weighting methodology. Therefore, instead of creating equally-weighted (ew) portfolios as reported in previous sections, we evaluate market value-weighted (vw) strategies. It has the consequence of losing the size premium that an equally-weighting scheme implies. Therefore, we should expect a lower expected return when stocks' weights are computed using the market capitalization for every security. Figures 10 and 11 show two box-plots showing portfolio returns' distributions for four different strategies for both an ew method and a vw method. For each strategy, we select the best performer definition reported in Section 6.2. Thus, for the Low Volatility, the Momentum, the Quality, and the Value anomaly we take the performance of portfolios sorted on Idiosyncratic Volatility, Quality Momentum, Quality, and Operating Income-to-Enterprise Value, respectively.

Figure 10 displays the returns' distributions for the difference portfolios, while Figure 11 shows the returns' distributions for the top decile portfolios. In general, there is an increase in the spread of returns when the vw approach is implemented. The blue candles exhibit a higher maximum return but also a lower minimum return. The first quartile is usually lower for the vw portfolios' returns than for the ew strategies. The same applies to the third quartile in the distribution. However, there is no evidence of a higher value for both the median and the mean of returns. In certain cases, we could expect a higher expected excess return as in the Low Volatility anomaly: Figure 10 shows that the red point in the blue candle, which represents the mean of the excess of returns, is higher than the red point in the pink candle. In both Figures, the monthly mean of the excess of returns is higher in ew portfolios for the Momentum, the Quality, and the Value anomaly.

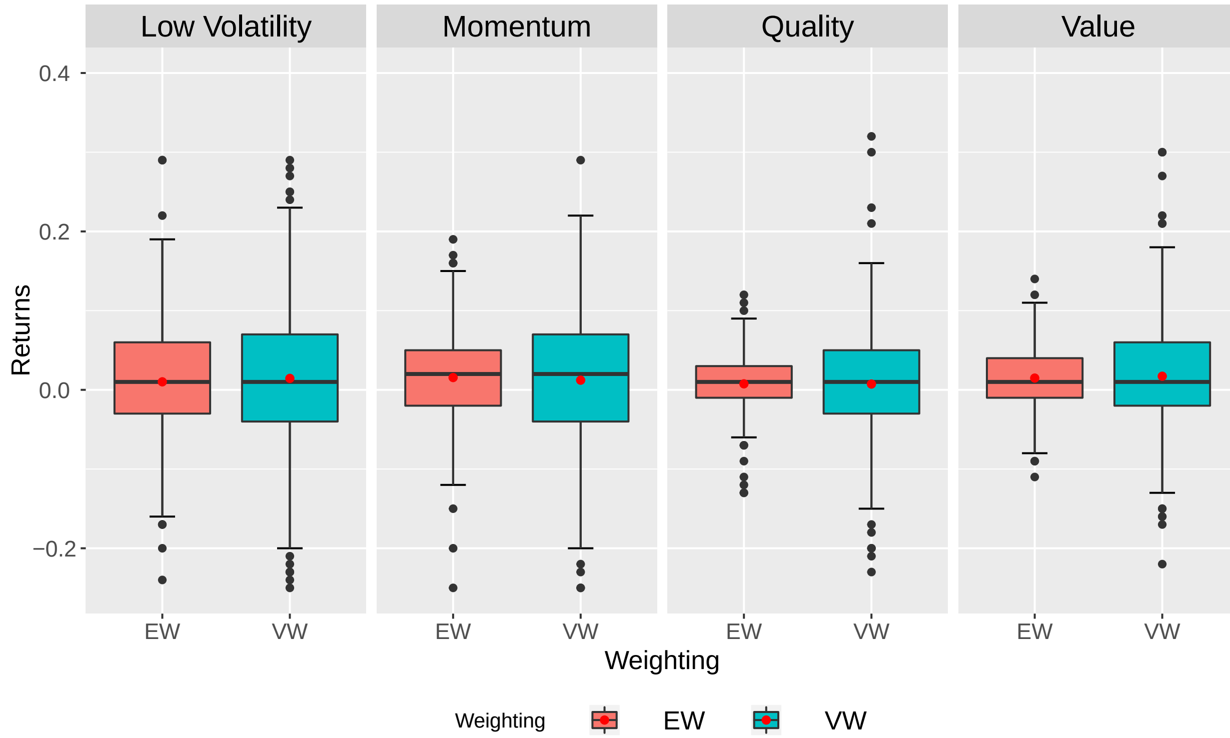

Figure 10
Value-weighted vs equally-weighted portfolio returns' box-plot for the difference portfolios. This figure compares the returns distribution for the difference portfolios in each strategy based on an equally-weighting method and a value-weighting method. For each strategy, we select the best performer definition reported in Section 6.2. Thus, for the Low Volatility, the Momentum, the Quality, and the Value anomaly we take the performance of portfolios sorted on Idiosyncratic Volatility, Quality Momentum, Quality, and Operating Income-to-Enterprise Value, respectively. Portfolios are rebalanced monthly in both methodologies. The red point represents the average monthly return for the whole sample period. The returns' distributions are generated using return data from January 2000 to December 2018.

It means that the vw approach for single-factor portfolios lowers the expected excess returns at the expense of higher risk. Thus, the risk-return trade-off is reduced significantly. Table XXXXI in the Appendix illustrates numerically the results shown in Figures 10 and 11. For instance, for the Quality Momentum strategy, the return for the top decile portfolio and the difference portfolio decreases from 13% (See Table VI) to 8% (See Table XXXXI) and from 18% to 14%, respectively. For the Value and the Quality anomaly, the returns are also materially reduced. However, for the Low Volatility anomaly the story is the inverse: the average excess return for the top decile portfolio and the difference increases from 5% to 7% and from 8% to 18%, respectively. Thus, on the overall, Table XXXXI indicates that an active investor wishing to create single- and multi-factor portfolios should form portfolios by following an equally-weighted approach rather than a value-weighted approach and also benefit from the size premium indirectly.

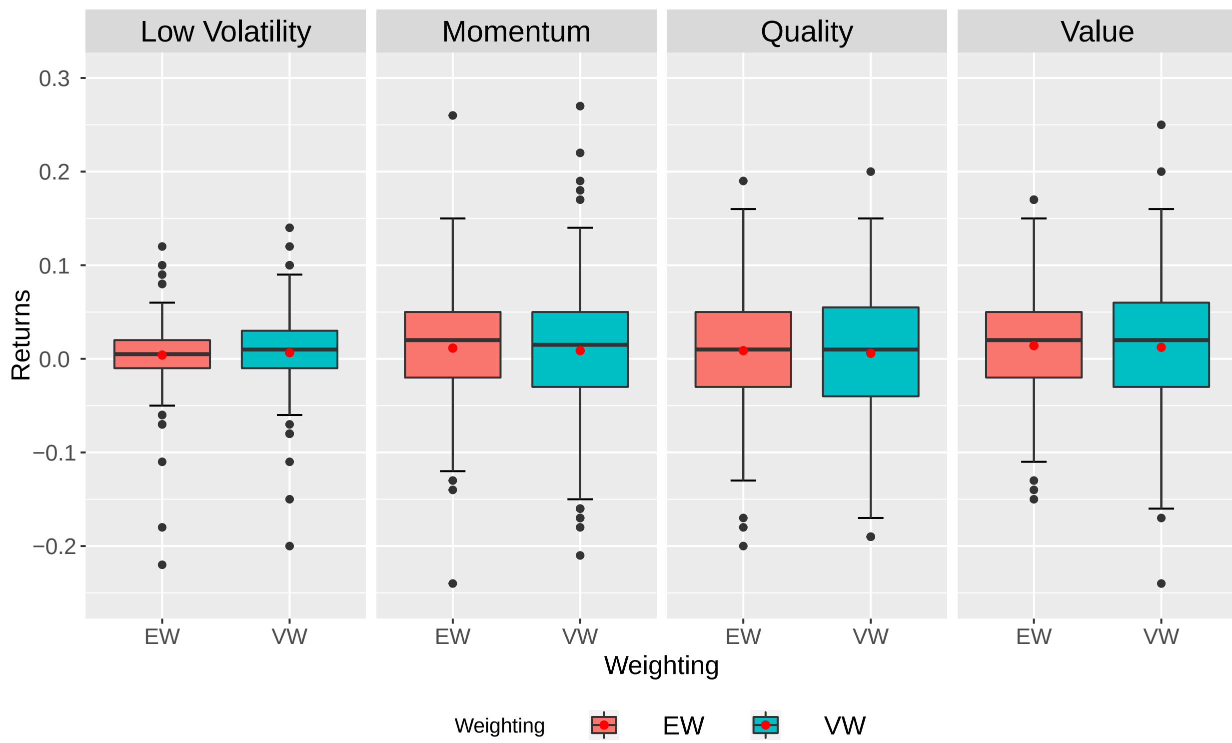

Figure 11
Value-weighted vs equally-weighted portfolio returns' box-plot for the top decile portfolios. This figure compares the returns distribution for the top decile portfolios in each strategy based on an equally-weighting method and a value-weighting method. For each strategy, we select the best performer definition reported in Section 6.2. Thus, for the Low Volatility, the Momentum, the Quality, and the Value anomaly we take the performance of portfolios sorted on Idiosyncratic Volatility, Quality Momentum, Quality, and Operating Income-to-Enterprise Value, respectively. Portfolios are rebalanced monthly in both methodologies. The red point represents the average monthly return for the whole sample period. The returns' distributions are generated using return data from January 2000 to December 2018.

7.4 Regression outputs for long-only multi-factor portfolios

In Sections 6.3 and 6.4, we only report the performance statistics for long-only multi-factor portfolios and the advantages of applying a dynamic asset allocation strategy versus the Benchmark Index and the Market portfolio. However, we do not know whether the pattern in the multi-factor portfolios' average returns persists after controlling for systematic risk factors. Thus, in this Section, we document the alphas generated for each strategy when the portfolios' excess returns are regressed against the CAPM Model, the Fama-French Three-Factor Model, and the Carhart Four-Factor Model. Table XXXI shows the regressions outputs over the three asset pricing models when long-only multi-factor portfolios are considered. To remind, in Section 6.2, we demonstrate that hardly any long-only single-factor portfolios could generate an alpha after controlling even for the Market portfolio. For those strategies, alphas become negative and significant when the SMB, the HML, and the MOM are included as explanatory variables too. Table XXXI illustrates that long-only multi-factor portfolios can generate statistically significant and positive alphas after controlling for the Market portfolio. Quality Plus Value, Momentum Plus Value, Value Plus Low Volatility, and the Multifactor portfolio are the most robust strategies. RMRF's loadings, although highly significant, are not as high as those reported for long-only single-factor portfolios. Therefore, by combining strategies, an investor can generate portfolios that are not strongly correlated to the Market with a potential alpha generation ability.

Table XXXI
Regression Outputs for LatAm Long-Only Multi-Factor Portfolios

This table displays the regression outputs for seven long-only multi-factor portfolios formed by equally combining Momentum, Value, Low Volatility, and Quality using a portfolio blending approach. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample contains 614 unique companies between 2000 and 2018.

	Quality + Low Vol	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Vol	Value + Low Vol	Multifactor
Panel A: Regression Against the CAPM							
Alpha	0.13	**0.40***	0.25	**0.57****	0.30	**0.45****	**0.35***
RMRF	**0.49*****	**0.68*****	**0.70*****	**0.65*****	**0.46*****	**0.44*****	**0.57*****
Adj-R^2	0.64	0.68	0.71	0.66	0.56	0.56	0.69
Panel B: Regression Against the Fama-French Three-Factor Model							
Alpha	**-0.28***	-0.11	**-0.32***	-0.04	-0.21	0.00	-0.16
RMRF	**0.64*****	**0.85*****	**0.90*****	**0.86*****	**0.65*****	**0.60*****	**0.75*****
SMB	**0.45*****	**0.53*****	**0.62*****	**0.65*****	**0.57*****	**0.48*****	**0.55*****
HML	**0.19*****	**0.32*****	**0.29*****	**0.35*****	**0.21*****	**0.24*****	**0.27*****
Adj-R^2	0.74	0.78	0.82	0.81	0.72	0.70	0.82
Panel C: Regression Against the Carhart Four-Factor Model							
Alpha	-0.23	-0.05	**-0.43****	-0.15	**-0.32****	0.06	-0.19
RMRF	**0.64*****	**0.85*****	**0.91*****	**0.87*****	**0.66*****	**0.60*****	**0.75*****
SMB	**0.45*****	**0.52*****	**0.63*****	**0.66*****	**0.59*****	**0.47*****	**0.55*****
HML	**0.15*****	**0.28*****	**0.37*****	**0.41*****	**0.28*****	**0.20*****	**0.28*****
MOM	**-0.06***	-0.06	**0.11*****	**0.11*****	**0.11*****	**-0.06****	0.03
Adj-R^2	0.74	0.78	0.83	0.82	0.73	0.71	0.82

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

However, when we count the Size, the Value, and the Momentum risk factor in explaining the average excess returns in long-only multi-factor portfolios, Alphas are now close to zero and, in some cases, in negative territory. Still, Quality Plus Value, Momentum Plus Value, Value Plus Low Volatility, and the Multifactor portfolio are the strategies most challenging to be explained by these asset pricing models. This fact has severe practical consequences: An investor could focus only on these pairs to generate consistent abnormal excess returns concerning their Benchmarks. Thus, to some extent, all multi-factor portfolios share characteristics of a Size and a Value effect. In other words, these strategies are successful as multi-factor portfolios are tilted towards small-caps and cheap stocks, but unsurprisingly with a neutral exposure to Momentum.

Table XXXII
Regression Outputs for LatAm Long-Only Multi-Factor Portfolios with a Dynamic Asset Allocation Strategy

This table displays the regression outputs for seven long-only multi-factor portfolios formed by equally combining Momentum, Value, Low Volatility, and Quality using a portfolio blending approach and applying a dynamic asset allocation strategy. RMRF is the excess return on all firms in the sample incorporated in Brazil, Mexico, Chile, Peru, and Colombia. SMB, HML, and MOM are Fama and French's factor-mimicking portfolios for size, book-to-market equity, and Momentum for LatAm equity markets. Alphas are reported in percentage. The data sample contains 614 unique companies between 2000 and 2018.

	Quality + Low Vol	Quality + Value	Quality + Momentum	Momentum + Value	Momentum + Low Vol	Value + Low Vol	Multifactor
Panel A: Regression Against the CAPM							
Alpha	**0.71*****	**0.85*****	**0.75*****	**0.97*****	**0.84*****	**0.93*****	**0.84*****
RMRF	**0.20*****	**0.27*****	**0.32*****	**0.31*****	**0.24*****	**0.19*****	**0.25*****
Adj-R^2	0.22	0.23	0.26	0.25	0.24	0.20	0.25
Panel B: Regression Against the Fama-French Three-Factor Model							
Alpha	**0.37****	**0.39***	0.23	**0.46***	**0.44****	**0.60*****	**0.41****
RMRF	**0.33*****	**0.44*****	**0.51*****	**0.49*****	**0.38*****	**0.31*****	**0.41*****
SMB	**0.38*****	**0.51*****	**0.56*****	**0.56*****	**0.43*****	**0.37*****	**0.47*****
HML	**0.12*****	**0.19*****	**0.25*****	**0.25*****	**0.19*****	**0.13*****	**0.19*****
Adj-R^2	0.35	0.38	0.41	0.41	0.39	0.34	0.41
Panel C: Regression Against the Carhart Four-Factor Model							
Alpha	0.27	0.20	-0.04	0.18	0.25	**0.49*****	0.22
RMRF	**0.34*****	**0.45*****	**0.52*****	**0.51*****	**0.39*****	**0.32*****	**0.42*****
SMB	**0.39*****	**0.53*****	**0.59*****	**0.59*****	**0.45*****	**0.39*****	**0.49*****
HML	**0.19*****	**0.31*****	**0.42*****	**0.43*****	**0.31*****	**0.20*****	**0.31*****
MOM	**0.11*****	**0.19*****	**0.28*****	**0.28*****	**0.19*****	**0.11*****	**0.19*****
Adj-R^2	0.38	0.43	0.50	0.51	0.47	0.37	0.48

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

On the other hand, Table XXXII shows that when a dynamic asset allocation strategy is employed simultaneously to multi-factor portfolios, neither the CAPM nor the Fama-French Three-Factor Model can explain the cross-sectional variation in average excess returns. Generated alphas are statistically significant at the 1% level and positive, despite all systematic risk factors gather positive and significant loadings on all multi-factor portfolios. Surprisingly, the Adj-R^2 stays low, below the 50% even for the Carhart Four-Factor Model. Therefore, a strategy that actively selects among multi-factor portfolios and fixed income securities seems to be a big challenge for the most common asset pricing models. Even for the Carhart

Four-Factor Model, despite Alphas are not significant, a dynamic asset allocation strategy can generate positive abnormal excess returns. Alphas are reduced as the MOM factor captures the underlying nature of the strategy, which is based on Absolute Momentum.

7.5 Equally-weighted systematic risk factors and the effects of liquidity constraints

7.5.1 Equally-weighted systematic risk factors

Now, we consider some checks for the systematic risk factors when equally-weighted returns are used instead of value-weighted returns for the RMRF, SMB, HML, and MOM. It is important to note that the construction of systematic risk factors is as crucial as the construction of the strategies. In the end, these are the variables that assess the attractiveness of each portfolio from a statistical point of view. Table XXXIII shows the monthly descriptive statistics for four systematic risk factors from January 2000 to December 2018 using an equally-weighted approach. Compared to Table IV in Section 6.1, equally-weighted systematic risk factors are also robust, but some changes apply. For instance, SMB's risk premium is no longer significant compared to its value-weighted version, and HML's average return is now significant at the 1% level. The risk premium for the UMD risk factor is significant, no matter if an equally-weighted or value-weighted approach is used. Finally, the excess return for the Market factor also losses significant during the whole sample period when an equally-weighted method is applied: its average monthly return drops to 0.34% ($t = 0.80$) per month. Thus, the risk premiums for the SMB, the HML, and the UMD factor are 0.16% ($t = 0.83$), 0.51% ($t = 2.84$), and 0.62% ($t = 2.03$) per month, respectively.

Table XXXIII
Performance Statistics of LatAm EW Systematic Risk Factors

This table gives the monthly descriptive statistics for four systematic risk factors spanning from January 2000 to December 2018 using the whole sample in LatAm equity markets. SMB, HML, and UMD are equally-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return using the whole sample of companies in the LatAm region.

Factor	Average	Std	T-Stat for		Pearson Correlations			
Portfolio	Returns	Deaviation	Mean = 0	P-Value	SMB	HML	UMD	RMRF
SMB	0.16%	2.91%	0.83	0.41	1.00			
HML	**0.51%*** **	2.70%	2.84	0.01	-0.32	1.00		
UMD	**0.62%** **	4.60%	2.03	0.04	0.26	-0.17	1.00	
RMRF	0.34%	6.42%	0.80	0.42	-0.28	0.16	-0.40	1.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table XXXIV also reports the performance statistics of equally-weighted systematic risk factors but for two different sub-sample periods. Panel A shows the average values of risk premiums from January 2000 to December 2008, and panel B shows the average risk premiums from January 2009 to December 2018. All equally-weighted factors have also experienced periods of excellent and weak performance. For instance, the period from January 2009 to December 2018 was also weak for most systematic risk factors in LatAm. SMB had a negative average risk premium of 0.17% per month; while HML and UMD had weak and not significant returns. The Market factor had an opaque behavior of just 0.27% per month during this period. Thus, none systematic factor is statistically significant at any confidence level. From January 2000 to December 2018, equally-weighted average risk premiums are more consistent and stable. HML and UMD reported outstanding and significant average risk premiums equal to 0.86% ($t = 3.08$) and 0.75% ($t = 1.97$) per month, respectively. Despite the average risk premium of the Market portfolio and the Size factor is not statistically significant, they are modest at a 0.43% ($t = 0.62$) and 0.53% ($t = 1.56$) per month, respectively.

Table XXXIV

Subsample Performance Statistics of LatAm EW Systematic Risk Factors

This table gives the monthly descriptive statistics for four systematic risk factors spanning from January 2000 to December 2018 using the whole sample in LatAm equity markets. SMB, HML, and UMD are value-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return using the whole sample of companies in the LatAm region.

	Average Returns	Std Deviation	T-Stat for Mean = 0	P-Value	Average Returns	Std Deviation	T-Stat for Mean = 0	P-Value
Panel A: January 2000 to December 2008					**Panel B: January 2009 to December 2018**			
SMB	0.53%	3.52%	1.56	0.12	-0.17%	2.18%	-0.86	0.39
HML	**0.86%****	2.89%	3.08	0.03	0.19%	2.49%	0.85	0.40
UMD	**0.75%****	3.93%	1.97	0.05	0.50%	5.14%	1.07	0.29
RMRF	0.43%	7.19%	0.62	0.54	0.27%	5.67%	0.52	0.61

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

7.5.2 Effects of liquidity constraints on systematic risk factors

In Section 4, we use a liquidity filter of just US$30,000 on a three-month rolling-window basis in order to exclude companies that do not trade at all. Although the liquidity constraint is low, we want to test all strategies with high and low liquidity stocks. It makes the analysis stronger but can create biases as our results may be affected by a liquidity premium. However, in this section, we show that by applying stronger liquidity constraints on the creation of Fama-French's systematic risk factors, our results are still robust. Thus, Tables XXXV and XXXVI show the monthly descriptive statistics for three systematic risk factors spanning from January 2000 to December 2018 by applying five different liquidity constraints to the sample. Liquidity constraints are set to consider only companies with an average daily volume of US$500,000, US$1,000,000, US$3,000,000, US$5,000,000, and US$10,000,000 during the total sample period. Accordingly, the second column of Tables XXXV and XXXVI displays the number of companies left after applying the liquidity filter. Descriptive statistics are also shown into three different intervals: for the whole sample period in Panel A, from January 2000 to December 2008 in Panel B, and from January 2009 to December 2018 in Panel C.

Results on Table XXXV indicate that the relation regarding liquidity and average excess returns is inverse for the equally-weighted systematic risk factors. Thus, looking at the whole sample period, if the constraint is more restringing in having stocks with higher liquidity, then the higher the risk premiums. This phenomenon applies to all three systematic risk factors, being the Momentum the strongest among all. However, the higher the risk premiums are, the higher the standard deviation in all risk factors. This fact should also be expected as the number of companies is reduced significantly and erodes the potential diversification benefits. There are a few occasions when the risk factors are statistically significant. Nevertheless, the positive sign across all liquidity filters indicates that all effects are still present in the most highly liquid stocks in LatAm equities. As previously reported, all factors have experienced periods of excellent and weak performance. For instance, the period from January 2009 to December 2018 was perhaps the most challenging for the Value effect. Panel C of Table XXXV shows that HML had a particularly bad performance during the post-crisis cycle, but the Momentum effect performed brilliantly mainly within highly liquid stocks. Therefore, in periods of strong performance among factors, it is better to have exposure to those companies that are easily traded.

Results on Table XXXVI are mixed, mainly with the SMB factor. Panel B shows that the more liquid stocks experience a negative Size effect during the pre-crisis period, but recovered astonishingly after the turmoil. Momentum depicts a similar pattern, but it is stronger than the Size effect. For value-weighted returns, HML's negative performance is worsening. Even for the whole sample period, the Value effect is not present among the highly liquid stocks in LatAm equities, strongly influenced by the performance of the last decade. Regarding SMB and UMD, value-weighted average returns show that both effects are still present but less consistent compared to the equally-weighted counterparts. Thus, it seems that highly liquid stocks also benefits from the Size premium reported in Section 7.3.

Table XXXV
Equally-Weighted Systematic Risk Factors with Liquidity Constraints

This table gives the monthly descriptive statistics for three systematic risk factors spanning from January 2000 to December 2018 by applying five different liquidity constraints to the sample. SMB, HML, and UMD are equally-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). Liquidity constraints are set to consider only companies with an average daily volume of US$500,000, US$1,000,000, US$3,000,000, US$5,000,000, and US$10,000,000 during the total sample period. Thus, the second column illustrates the number of companies left after applying the liquidity filter. Descriptive statistics are also shown into three different intervals: for the whole sample period in Panel A, from January 2000 to December 2008 in Panel B, and from January 2009 to December 2018 in Panel C.

Liquidity	# of	Risk Premium			Std Deviation			T-Stat			P-Value		
Filter	Companies	SMB	HML	UMD	SMB	HML	UMD	SMB	HML	UMD	SMB	HML	UMD
Panel A: All Sample Period													
US$ 500,000	337	**0.39%****	0.29%	0.39%	2.69%	3.22%	5.32%	2.17	1.34	1.12	0.03	0.18	0.27
US$ 1,000,000	269	0.25%	0.37%	0.49%	2.88%	3.74%	5.52%	1.31	1.51	1.34	0.19	0.13	0.18
US$ 3,000,000	169	0.38%	0.18%	**0.88%****	3.83%	4.64%	5.85%	1.50	0.58	2.26	0.14	0.56	0.02
US$ 5,000,000	126	0.42%	0.18%	**0.99%*****	4.01%	4.91%	5.86%	1.58	0.55	2.56	0.12	0.58	0.01
US$ 10,000,000	69	0.51%	0.37%	0.67%	5.46%	6.39%	6.65%	1.41	0.87	1.51	0.16	0.39	0.13
Panel B: From January 2000 to December 2008													
US$ 500,000	337	**0.71%****	**0.80%*****	0.37%	3.13%	3.31%	4.62%	2.36	2.52	0.84	0.02	0.01	0.40
US$ 1,000,000	269	0.51%	**0.96%*****	0.43%	3.28%	4.02%	4.89%	1.63	2.48	0.92	0.11	0.01	0.36
US$ 3,000,000	169	**0.66%***	0.67%	0.59%	4.16%	4.94%	5.39%	1.66	1.42	1.13	0.10	0.16	0.26
US$ 5,000,000	126	0.54%	0.60%	0.84%	4.32%	5.25%	5.38%	1.30	1.19	1.62	0.20	0.24	0.11
US$ 10,000,000	69	0.01%	0.40%	0.03%	5.48%	6.37%	5.85%	0.02	0.64	0.05	0.98	0.52	0.96
Panel C: January 2009 to December 2018													
US$ 500,000	337	0.09%	-0.18%	0.41%	2.19%	3.07%	5.89%	0.47	-0.63	0.76	0.64	0.53	0.45
US$ 1,000,000	269	0.01%	-0.15%	0.54%	2.47%	3.41%	6.04%	0.05	-0.49	0.98	0.96	0.62	0.33
US$ 3,000,000	169	0.12%	-0.27%	**1.14%****	3.51%	4.32%	6.25%	0.39	-0.67	2.00	0.70	0.50	0.05
US$ 5,000,000	126	0.31%	-0.20%	**1.13%****	3.73%	4.56%	6.29%	0.91	-0.48	1.98	0.36	0.63	0.05
US$ 10,000,000	69	**0.96%***	0.34%	**1.24%***	5.43%	6.44%	7.27%	1.93	0.59	1.87	0.06	0.56	0.06

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table XXXVI
Value-Weighted Systematic Risk Factors with Liquidity Constraints

This table gives the monthly descriptive statistics for three systematic risk factors spanning from January 2000 to December 2018 by applying five different liquidity constraints to the sample. SMB, HML, and UMD are value-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). Liquidity constraints are set to consider only companies with an average daily volume of US$500,000, US$1,000,000, US$3,000,000, US$5,000,000, and US$10,000,000 during the total sample period. Thus, the second column illustrates the number of companies left after applying the liquidity filter. Descriptive statistics are also shown into three different intervals: for the whole sample period in Panel A, from January 2000 to December 2008 in Panel B, and from January 2009 to December 2018 in Panel C.

Liquidity	# of	Risk Premium			Std Deviation			T-Stat			P-Value		
Filter	Companies	SMB	HML	UMD	SMB	HML	UMD	SMB	HML	UMD	SMB	HML	UMD
Panel A: All Sample Period													
US$ 500,000	337	**0.42%****	0.05%	0.26%	2.89%	3.56%	5.56%	2.21	0.22	0.71	0.03	0.83	0.48
US$ 1,000,000	269	0.30%	0.06%	0.35%	3.09%	4.15%	6.03%	1.45	0.22	0.89	0.15	0.82	0.38
US$ 3,000,000	169	**0.42%***	-0.14%	0.58%	3.30%	4.64%	6.08%	1.92	-0.46	1.43	0.06	0.64	0.15
US$ 5,000,000	126	0.36%	-0.16%	**0.82%****	3.72%	5.14%	6.22%	1.45	-0.46	1.99	0.15	0.65	0.05
US$ 10,000,000	69	0.27%	-0.21%	0.49%	4.36%	5.28%	6.43%	0.94	-0.60	1.16	0.35	0.55	0.25
Panel B: From January 2000 to December 2008													
US$ 500,000	337	**0.54%***	0.36%	0.28%	3.25%	3.55%	5.07%	1.73	1.05	0.58	0.09	0.30	0.56
US$ 1,000,000	269	0.29%	0.52%	0.30%	3.73%	4.19%	5.38%	0.82	1.29	0.58	0.42	0.20	0.56
US$ 3,000,000	169	0.34%	0.08%	0.50%	3.92%	4.62%	5.43%	0.92	0.18	0.95	0.36	0.85	0.34
US$ 5,000,000	126	0.28%	-0.02%	0.71%	4.47%	5.70%	5.82%	0.65	-0.03	1.26	0.52	0.97	0.21
US$ 10,000,000	69	-0.36%	0.01%	-0.08%	5.27%	5.61%	5.72%	-0.70	0.02	-0.14	0.49	0.99	0.89
Panel C: January 2009 to December 2018													
US$ 500,000	337	0.32%	-0.22%	0.24%	2.54%	3.57%	5.98%	1.37	-0.68	0.44	0.17	0.50	0.66
US$ 1,000,000	269	0.30%	-0.35%	0.40%	2.38%	4.09%	6.59%	1.37	-0.95	0.67	0.17	0.34	0.51
US$ 3,000,000	169	0.49%	-0.34%	0.65%	2.65%	4.66%	6.63%	2.01	-0.81	1.07	0.05	0.42	0.29
US$ 5,000,000	126	0.43%	-0.28%	0.92%	2.89%	4.59%	6.58%	1.61	-0.67	1.53	0.11	0.50	0.13
US$ 10,000.,	69	**0.83%*****	-0.41%	1.01%	3.26%	4.99%	6.99%	2.80	-0.90	1.58	0.01	0.37	0.12

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

However, it is not clear as it is in Table XXXV, whether the value-weighted risk factors enjoy the inverse relation between liquidity and expected excess returns reported for the equally-weighted returns, at least for the SMB and the HML factors, but we can be sure that by applying a more aggressive liquidity filter to our sample data of companies in LatAm, most effects are still intact for both ways of computing returns. This conclusion is stronger, of course, for the equally-weighted scenario.

8 Conclusion

The development of new investment strategies has been focused on the developed world where markets are more liquid and transparent. In the last couple of years, the research of anomalies in emerging markets has been expanding as inefficiencies are present, and investment opportunities are equally promising. However, there is a lack of interest by some sophisticated investors in the implementation and execution of these strategies in LatAm equities due to their size compared to the global market. Therefore, this research is part of a significant effort to study the behavior of equity markets in Latin America and bring into light the opportunities that an investor may face by quantitatively investing in these markets. Thus, we consider US Dollar stock returns between January 2000 and December 2018 in five different countries to document the existence of anomalies that are present in other developed and emerging market countries. First, we start by demonstrating that Size, Book-to-Market Equity, and Momentum can explain the cross-section of stock returns in LatAm equities. We then create a Size, a Value, and a Momentum factor to evaluate each anomaly individually.

Second, we confirm the profitability of investment strategies based on Value, Momentum, Low Volatility, and Quality in Latin America. We demonstrate that stocks that have outperformed in the last twelve months continue to doing so, Value stocks earn higher excess returns than Growth stocks, Low Volatile stocks outperform risky stocks, and Quality companies' returns surpass Junk companies'. Different definitions for each anomaly were tested, and the empirical evidence reported shows that strategies based on characteristics different from the traditional definitions generate better returns. For instance, for the Value effect, high Operating Profit-to-Enterprise Value stocks earn higher excess returns compared to high Book-to-Market companies. Additionally, for the Momentum effect, the path of the past year return matters, and a Quality Momentum strategy delivers better results compared to Generic Momentum strategies. We also find that Value and Momentum are the most potent effects in the targeted markets and Low Volatility and Quality the weakest.

The performance of single-factor portfolios can be improved by combining all the anomalies into multi-factor portfolios. Six different portfolios were created by blending simultaneously pairs strategies based on Value, Momentum, Low Volatility, and Quality, and a multi-factor strategy that invests equally into all anomalies was also produced. We statistically demonstrate that multi-factor strategies are superior to single-factor portfolios as there is a more significant improvement in the Sharpe ratio when risk factors are combined to multi-factor portfolios as denoted by the size of the GRS Test statistics. Therefore, we show that due to low correlations among strategies, long-only multi-factor portfolios' Sharpe ratios are enhanced significantly when two or more strategies are put together. We also consider the two most used approaches to multi-factor portfolio construction: the portfolio blending approach and the signal blending approach. Although the difference is not significant when looking at the Sharpe ratios and average excess returns, the portfolio blending approach is better to multi-factor portfolio construction. However, we consider the implementation of one approach or the other would depend on the investor's specific investment objectives such as the reduction in turnover and transaction costs which favors a signal blending approach or the increase in Sharpe ratio which benefits the portfolio blending approach.

We further leverage the understanding of Absolute Momentum to propose a dynamic asset allocation strategy to actively decide to invest 100% in multi-factor portfolios or 100% in the Barclays US Aggregate Bond Index according to an Absolute Momentum signal applied to the MSCI Emerging Markets Latin America Index. The idea behind this strategy is to retain the upside potential in bull markets while going cautious during bear markets. Our results show that the implementation of Absolute Momentum serves as a capital preserving strategy in the long-term: the number of months with positive returns is improved close to 70% and, surprisingly, the beta for each multi-factor portfolio concerning the Benchmark is closer to zero. Furthermore, there is a vast improvement in the Sharpe ratio. The risk-return trade-off increases dramatically above the one threshold in most cases. Additionally, we illustrate that applying a dynamic asset allocation strategy reduces the exposure to extremely adverse events and makes the distribution of monthly returns to be positively skewed.

A set of robustness checks were performed to look at the reported strategies from different points of view and get a better understanding of the properties for each of them. We first analyze all strategies at different time intervals from January 2000 to December 2018. We then show the results of quintile portfolios instead of decile portfolios and, lastly, we illustrate the performance statistics of value-weighted decile portfolios as an alternative of equally-weighted portfolios. Thereby, we demonstrate that single-factor portfolios may pose long periods of underperformance compared to both the Benchmark and the Market portfolio. However, the implementation of multi-factor portfolios do not exempt periods of lousy performance, but the execution of a dynamic asset allocation strategy does improve the average expected returns in all business cycles. Finally, we prove that anomalies are still present when portfolios are formed on a value-weighted basis and using quintiles instead of deciles. However, the results are weaker as the portfolios do not benefit from the size premium and are less tilted to the factors as more diversification is present.

Summing up, the empirical evidence reported in this paper helps to answer the central question of the research and addresses the title for this thesis: does the implementation of quantitative investment strategies in LatAm equity markets challenge the Efficient Market Hypothesis (EMH) drawn by Eugene Fama in the 1970s? The answer is yes! Throughout the document we extensively report evidence against both the semi-strong and the weak form of the EMH: obtaining abnormal excess returns through the implementation of Momentum and Low Volatility strategies through the use of past returns is clearly a kick-in-the-seat-of-the-pants to the weak form of the Hypothesis, whilst using fundamental data in the execution of Value and Quality strategies also brings into light evidence to question the validity of the semi-strong form of the EMH. All this means that by systematically using available public and material information, an investor could improve the efficient frontier he is attached to. We do not consider the implication of transaction costs in this research. Therefore, future developments should include the execution of all the strategies net of trading costs. However, we clearly show that any strategy from single-factor portfolios to a dynamic asset allocation strategy beat substantially a passive investment strategy that invests in the MSCI Emerging Markets Latin America Index.

9 Appendix

9.1 Total number of companies and the proportion of individual countries

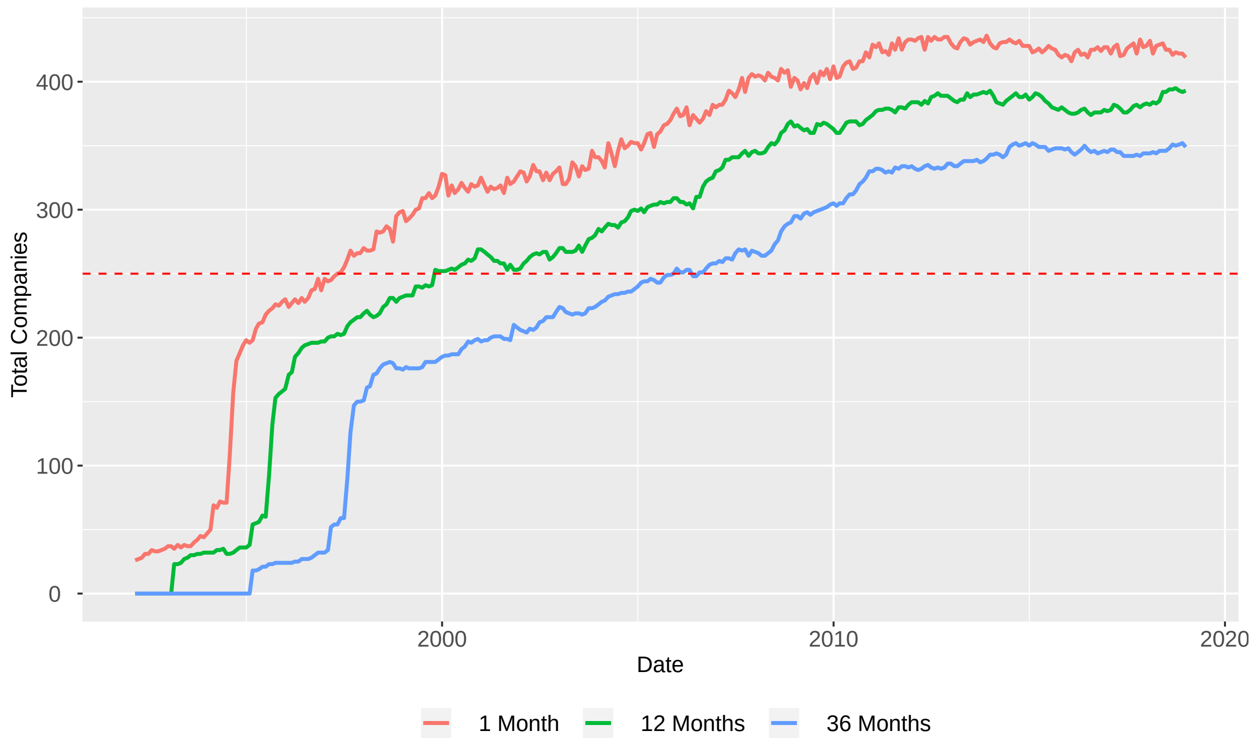

Figure 12
Total number of companies in LatAm equity markets from January 1992 with available returns. This figure shows the number of total companies in the five countries in this region with available returns data. The pink line represents the evolution of companies with at least one month of return data, the green line represents the number of companies with at least twelve months of return data, and the blue line represents the total number of companies with at least thirty-six months of returns data.

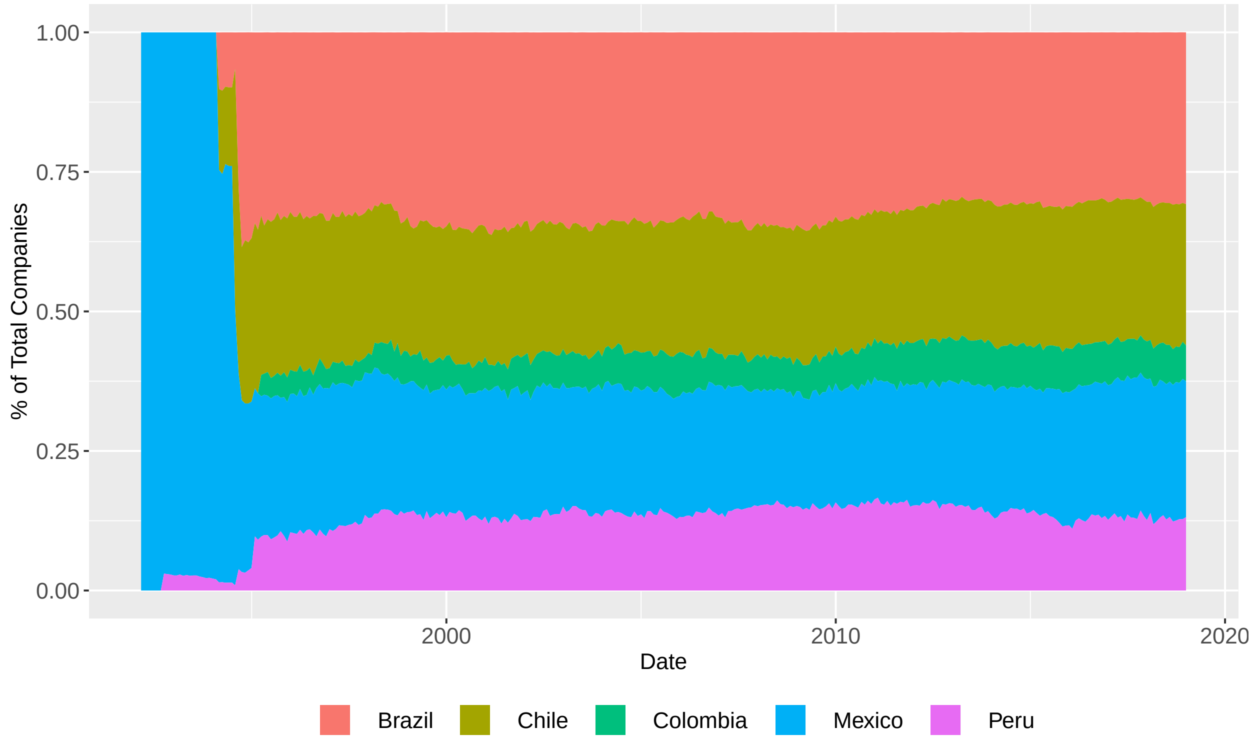

Figure 13
Historical country proportion per number of total companies. This figure shows the evolution of the proportion of each country into the total number of companies available to invest in LatAm from January 1992 to December 2018.

9.2 Performance statistics of US systematic risk factors

Table XXXVII
Performance Statistics of US Systematic Risk Factors

This table gives the monthly descriptive statistics for four systematic risk factors spanning from January 2000 to December 2018 in US equity markets. SMB, HML, and UMD are value-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return. Factors' returns are taken directly from Kenneth French's website.

Factor Portfolio	Average Returns	Std Deaviation	T-Stat for Mean = 0	P-Value	Pearson Correlations			
					SMB	HML	UMD	RMRF
SMB	0.25%	3.31%	1.16	0.25	1.00			
HML	0.27%	3.14%	1.28	0.20	-0.26	1.00		
UMD	0.21%	5.33%	0.60	0.55	0.11	-0.17	1.00	
RMRF	0.38%	4.35%	1.33	0.18	0.26	-0.06	-0.35	1.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table XXXVIII
Subsample Performance Statistics of US Systematic Risk Factors

This table gives the monthly descriptive statistics for four systematic risk factors spanning from January 2000 to December 2018 in US equity markets. SMB, HML, and UMD are value-weighted Fama and French's mimicking portfolios for Size, Book-to-Market Equity, and Momentum. These zero-cost portfolios are created using the methodology described in Eq (9), Eq (10), and Eq (11). RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return using the whole sample of companies in the LatAm region.

	Average Returns	Std Deviation	T-Stat for Mean = 0	P-Value	Average Returns	Std Deviation	T-Stat for Mean = 0	P-Value
Panel A: January 2000 to December 2018					**Panel B: January 2009 to December 2018**			
SMB	0.44%	4.11%	1.12	0.26	0.08%	2.38%	0.39	0.70
HML	**0.74%****	3.55%	2.17	0.03	-0.16%	2.66%	-0.67	0.50
UMD	0.69%	5.97%	1.19	0.24	-0.21%	4.68%	-0.50	0.62
RMRF	-0.42%	4.56%	-0.95	0.34	**1.11%*****	4.04%	3.00	0.00

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

9.3 *Annual returns of long/short and long-only strategies per year*

Table XXXIX
Annual Returns of Long/Short Strategies per Year

This table gives the annual returns for four long/short strategies spanning from 2000 to 2018 using the whole sample in LatAm equity markets. RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return. The Benchmark (Bmk) represents the annual performance for the MSCI Emerging Markets Latin America Index. The outperformance/underperformance is represented through the numbers' colors on the table. A long/short portfolio has outperformed the RMRF whenever a figure is printed in green. Contrarily, a long/short portfolio has underperformed the RMRF whenever a figure is printed in red.

Year	Momentum	Value	Low Volatility	Quality	Bmk	RMRF
2000	24.21%	52.88%	21.44%	-2.23%	-24.94%	-17.80%
2001	3.84%	33.96%	20.59%	36.98%	-11.90%	2.30%
2002	38.05%	4962%	46.15%	24.61%	-30.97%	-41.78%
2003	-10.01%	22.58%	-71.25%	-0.37%	61.54%	89.09%
2004	25.17%	-12.22%	-8.89%	-5.18%	30.72%	14.39%
2005	17.72%	-10.01%	-15.59%	6.01%	36.46%	25.72%
2006	4.21%	22.54%	-14.35%	27.77%	28.57%	31.69%
2007	54.34%	10.84%	-7.28%	-8.81%	37.30%	49.25%
2008	39.39%	56.94%	127.47%	-15.98%	-60.30%	-48.22%
2009	-42.78%	36.03%	-55.66%	11.58%	89.26%	91.87%
2010	-11.48%	-2.47%	3.09%	5.23%	9.05%	16.35%
2011	13.99%	29.66%	24.07%	34.61%	-25.00%	-11.95%
2012	28.54%	24.09%	17.61%	9.26%	2.82%	15.92%
2013	97.57%	24.67%	76.12%	0.41%	-16.99%	-10.13%
2014	59.76%	29.12%	31.48%	25.13%	-17.33%	-2.27%
2015	78.02%	11.49%	90.03%	32.59%	-35.03%	-15.22%
2016	-29.57%	-15.88%	-38.06%	-2.61%	22.19%	22.51%
2017	29.07%	-4.84%	6.85%	-10.10%	18.78%	30.73%
2018	16.04%	30.09%	13.94%	10.76%	-13.70%	2.16%

Table XXXX
Annual Returns of Long-Only Strategies per Year

This table gives the annual returns for four long-only strategies spanning from 2000 to 2018 using the whole sample in LatAm equity markets. RMRF represents the performance of a value-weighted equity index minus the US one-month T-bill return. The Benchmark (Bmk) represents the annual performance for the MSCI Emerging Markets Latin America Index. The outperformance/underperformance is represented through the numbers' color on the table. A long-only portfolio has outperformed the Bmk whenever a figure is printed in green. Contrarily, a long-only portfolio has underperformed the Bmk whenever a figure is printed in red.

Year	Momentum	Value	Low Volatility	Quality	Bmk	RMRF
2000	-22.26%	-3.37%	-12,.0%	-26.18%	-24.94%	-17.80%
2001	-6.70%	3.15%	-4.64%	-6.52%	-11.90%	2.30%
2002	-10.75%	7.47%	-13.44%	-14.74%	-30.97%	-41.78%
2003	79.15%	80.13%	-14.01%	75.23%	61.54%	89.09%
2004	81.63%	55.24%	48.66%	65.64%	30.72%	14.39%
2005	38.36%	11.92%	16.43%	28.23%	36.46%	25.72%
2006	39.49%	79.01%	27.33%	67.09%	28.57%	31.69%
2007	68.90%	61.35%	31.13%	38.47%	37.30%	49.25%
2008	-52.28%	-45.38%	-28.76%	-58.14%	-60.30%	-48.22%
2009	29.98%	115.05%	23.92%	87.47%	89.26%	91.87%
2010	34.63%	47.74%	40.39%	40.59%	9.05%	16.35%
2011	-24.43%	-13.37%	-15.52%	-4.17%	-25.00%	-11.95%
2012	30.72%	10.13%	23.67%	9.39%	2.82%	15.92%
2013	3.58%	-21.59%	3.75%	-24.11%	-16.99%	-10.13%
2014	-4.21%	-10.87%	-6.00%	-15.13%	-17.33%	-2.27%
2015	-19.33%	-35.48%	-18.03%	-29.27%	-35.03%	-15.22%
2016	11.10%	32.35%	3.38%	18.30%	22.19%	22.51%
2017	42.63%	30.54%	25.66%	16.89%	18.78%	30.73%
2018	-15.47%	-6.89%	-12.03%	-15.59%	-13.70%	2.16%

9.4 Descriptive statistics for value-weighted single-factor portfolios

Table XXXXI
Descriptive Statistics for Value-Weighted Single-Factor Portfolios

This table reports the descriptive statistics for 40 decile portfolios sorted on Quality Momentum $r_{12,1}$, Operating Profit-to-Enterprise Value, Idiosyncratic Volatility, and Quality. D1 contains the stocks with the undesired characteristics, whereas D10 contains stocks with the desired characteristics. D10-1 represents the difference portfolio. Excess returns are calculated on a value-weighted basis. The data sample for this strategy contains 614 unique companies between 1992 and 2018.

	D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**	**D10-1**
Panel A: Quality Momentum 12,1											
Excess Returns	-0.06	-0.01	0.03	-0.03	0.02	0.02	0.03	0.02	0.04	0.08	0.14
Standard Deviation	0.34	0.31	0.31	0.28	0.27	0.24	0.27	0.25	0.36	0.27	0.30
Max	0.32	0.24	0.32	0.20	0.35	0.16	0.35	0.20	0.23	0.27	0.29
Min	-0.43	-0.45	-0.35	-0.41	-0.26	-0.33	-0.35	-0.35	-1.08	-0.33	-0.29
Beta	0.95	0.98	0.94	0.95	0.86	0.81	0.87	0.81	1.10	0.80	-0.15
Sharpe Ratio	-0.17	-0.02	0.09	-0.10	0.06	0.09	0.11	0.07	0.12	0.28	0.47
T-Value	-5.23	-2.97	-0.30	-5.38	-1.12	-0.34	0.20	-0.92	0.43	3.86	3.56
IR	-0.35	-0.20	0.00	-0.36	-0.08	-0.05	0.01	-0.08	0.06	0.24	0.25
Panel B: Operating Profit-to-Enterprise Value											
Excess Returns	-0.05	0.03	-0.01	-0.01	0.00	0.03	0.04	0.03	-0.01	0.14	0.19
Standard Deviation	0.40	0.35	0.34	0.28	0.24	0.26	0.21	0.25	0.24	0.27	0.29
Max	0.47	0.36	0.35	0.25	0.18	0.20	0.14	0.21	0.16	0.25	0.30
Min	-0.42	-0.78	-0.49	-0.42	-0.37	-0.44	-0.28	-0.37	-0.32	-0.32	-0.34
Beta	1.15	1.09	1.05	0.95	0.73	0.81	0.60	0.81	0.78	0.86	-0.30
Sharpe Ratio	-0.11	0.07	-0.03	-0.02	0.00	0.11	0.20	0.11	-0.05	0.49	0.66
T-Value	-4.30	-0.75	-3.12	-3.37	-2.42	0.18	1.92	0.17	-3.73	8.29	5.08
IR	-0.27	-0.01	-0.18	-0.18	-0.18	0.00	0.07	0.00	-0.32	0.85	0.36
Panel C: One-Year Idiosyncratic Volatility											
Excess Returns	-0.10	0.01	0.01	-0.01	0.04	0.06	0.01	0.02	0.03	0.07	0.18
Standard Deviation	0.46	0.38	0.33	0.33	0.27	0.25	0.23	0.22	0.19	0.16	0.41
Max	0.44	0.35	0.25	0.23	0.27	0.20	0.16	0.18	0.14	0.14	0.82
Min	-0.88	-0.46	-0.39	-0.46	-0.31	-0.31	-0.28	-0.34	-0.26	-0.33	-0.37
Beta	1.36	1.22	1.07	1.11	0.89	0.82	0.70	0.69	0.53	0.39	-0.97
Sharpe Ratio	-0.21	0.02	0.02	-0.03	0.15	0.23	0.04	0.09	0.16	0.41	0.44
T-Value	-6.49	-2.06	-2.02	-3.61	1.08	3.13	-1.39	-0.41	1.15	5.18	2.77
IR	-0.38	-0.09	-0.11	-0.22	0.08	0.22	-0.11	-0.05	0.01	0.17	0.24
Panel D: Quality											
Excess Returns	-0.03	-0.05	-0.02	0.06	0.00	0.02	0.03	0.08	0.01	0.05	0.08
Standard Deviation	0.34	0.26	0.30	0.27	0.34	0.29	0.27	0.23	0.27	0.25	0.27
Max	0.36	0.19	0.24	0.40	0.33	0.33	0.20	0.20	0.21	0.20	0.32
Min	-0.31	-0.29	-0.45	-0.26	-0.87	-0.47	-0.41	-0.25	-0.35	-0.30	-0.26
Beta	1.00	0.79	0.99	0.89	1.07	0.93	0.89	0.75	0.80	0.82	-0.18
Sharpe Ratio	-0.08	-0.21	-0.06	0.23	-0.01	0.06	0.10	0.34	0.04	0.21	0.30
T-Value	-3.78	-6.72	-4.15	3.20	-2.70	-1.10	-0.04	5.99	-1.35	2.79	1.95
IR	-0.23	-0.44	-0.34	0.18	-0.12	-0.07	0.00	0.36	-0.12	0.18	0.13

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Rotterdam, 17*th* September 2019

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