Does time-varying systematic risk explain contrarian and momentum returns? Evidence from Latin America

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Abstract

Contrarian and momentum strategies have challenged the efficient market hypothesis as predictable patterns that allow investors to capitalize on past information and outperform market returns based on miss-reaction of naive investors. Market efficiency implies that agents are rational and, on average, the only way of achieving higher returns is by taking higher risks. This study investigates whether there are such predictable patterns in Emerging Markets and whether these profits are due to variation in time of systematic risk by estimating time-varying beta using a DCC model. Results indicate that these two strategies achieve higher returns because they are riskier and not because investors are irrational.

Keywords: Momentum and contrarian strategies; Overreaction and underreaction; MGARCH-DCC; Systematic time-varying market risk

JEL Codes: G11

1 Introduction

The academic literature on “fishing factors,” which attempts to identify empirical factors that generate consistent returns, has proposed at least 316 factors to explain the cross-section returns (Harvey et., 2016). However, only a few of these factors have shown consistent returns in the long-term and have an economic intuition behind their construction. The identification of risk factor that systematically produces a positive risk premium has been attempted by academics and practitioners during at least three decades. Among factors that have shown consistent returns, we find those based on contrarian and momentum strategies followed by investors who try to outperform the market returns. There are two mainstream research lines that have studied these strategies and specially the source of their profits. On the one hand, behavioral finance has compiled evidence against the efficient market hypothesis, and in favor of predictability of stock prices and irrationality in markets. On the other hand, market efficiency theorists have explained these anomalies from a rational and risk–reward approach.

From a behavioral approach, contrarian or value strategies rely on the overreaction hypothesis, according to which, investors tend to react more than they should to dramatic news events of firms (De Bondt and Thaler, 1985). Overreaction leads to miss-pricing of stocks far from their fundamental value and creates an opportunity to make abnormal profits by buying stocks that have been losers and by selling stocks that have been winners. Momentum strategies are based on the underreaction hypothesis, which points out that investors react slowly when new fundamental information arrives (Jegadeesh and Titman, 1993). Underreaction creates an opportunity to make abnormal profits by buying past winners and selling past losers.

Both hypotheses indicate that the miss-reaction will be eventually corrected and that prices reverse back to equilibrium. Contrarian investors expect prices to move in the opposite direction to their past record. De Bondt and Thaler (1985) show that stocks that performed poorly over the previous 3-5 years will perform better the next 3-5 years than stocks that performed well in the past. In this sense, overreaction is a long-term phenomenon. Momentum investors expect prices to continue in the same direction as in their recent price path. Jegadeesh and Titman (1993) show that stocks that have outperformed over the last 3-12 months continue to outperform for up to 12 months, thus underreaction is a short or medium-term phenomenon.

Evidence of contrarian investment profits due to overreaction are found in De Bondt and Thaler (1987) who reconsider their previous results and present new evidence that supports the overreaction hypothesis, and show that the size effect and differences in risk (measured using CAPM betas) do not explain these returns. Clare and Thomas (1995) find that past losers tend to outperform past winners in a holding period of 2 years in the UK and suggest that results may be related to firm size effects, while Dissanaike (1997) finds evidence of overreaction in larger and better known listed companies in the UK and finds no explanation from risk or bid-ask spread for contrarian profits. Kang et al. (2002) study contrarian strategies in the Chinese stock market and find that overreaction is related to firm specific information. Using the euro as the base currency Parikakis and Syriopoulos (2008) identify that the Turkish lira, the Brazilian real and the US dollar overreact and they suggest that this may be due to lack of volatility. Recent studies show that overreaction persists for different holding periods (Blackburn and Cakici, 2017; Lerskullawat and Ungphakorn, 2018) and even in the cryptocurrency market (Chevapatrakul and Mascia,2018).

Momentum strategies have been studied on several countries, industries, currencies and other asset classes following the Jegadeesh and Titman (1993) paper. Rouwenhorst (1998) finds that in 12 European countries, diversified portfolios of past medium term winners outperformed past medium term losers after correcting for risk. Jegadeesh and Titman (2001) extend their results and explore sources of potential explanations for momentum profits, they find that momentum returns are similar from their past study and these returns do not appear to be a consequence of data snooping or a compensation for risk. Van der Hart et al. (2003) find that momentum strategies generate significant excess returns in emerging markets and find no evidence of higher market risk or lower liquidity different momentum strategies.

Antoniou et al. (2013) study the relationship between price momentum and investor sentiment in the US stock market and find significant momentum profits when investors are too optimistic; moreover they show that this results are robust to firm size, risk and other potential explanations. Kosc et al. (2019) study the momentum and contrarian effects on cryptocurrency markets and find a clear and significant dominance of the short term contrarian effect over both momentum effect and the benchmark portfolios.

Contrary to behavioral explanations of contrarian and momentum profits Chan (1988) argues, based on an analysis grounded on CAPM beta, that the risks of winning and losing stocks in contrarian investment strategy are not constant. An explanation from market microstructure is found in Zarowin (1989) who also argues that the tendency of losers to outperform winners is not due to overreaction, but to the tendency of losers to be smaller sized firms than winners. Lo and Mackinlay (1990) argue that contrarian profits are due to lead-lag relations across securities and survivorship bias. Fama and French (1996) emphasize that, although the CAPM is not capable of explaining the returns of these two strategies, their three factor model rationalizes profits of contrarian strategies. However, Fama and French (2004) recognize that their three factor model is unable to explain patterns of returns related to the momentum effect.

In a study of international stocks Fama and French (2012) find strong momentum profits and proof that they are robust to risk after testing asset pricing models that include value, size and market risk. Asness et al. (2013) also consider international markets, but for both strategies and different asset classes and find that contrarian and momentum strategies generate abnormal returns in all countries. Moreover, in contrarian and momentum strategies, one asset class is positively correlated with those strategies in other asset-classes. In addition, the two strategies are inversely correlated. Therefore, momentum profits could simply be compensation for risk and might depend on cross-sectional differences and common factors (Jegadeesh and Titman, 1993; Fama and French, 1996; Grundy and Martin, 2001).

So far, the literature that studies whether risk factors are rewarded due to behavioral or risk exposure has not included the fact that risk and returns change over time. Usually, this literature has employed the CAPM as the main asset pricing model to provide evidence of the existence of efficiency in stock markets. However, if the fact that market risk (beta) changes over time is ignored (specially across the business cycle), then the results may be biased. For example, when there is a recession the marginal utility of wealth is high, then investors hedge against shortfalls in their level of wealth and consumption. This means that investors are not willing to take the same risk across the business cycle (Merton, 1973; Campbell and Cochrane, 1999) .This fact should be acknowledged by incorporating the nature of risk in a time-varying approach.

In this study we revisit whether contrarian and momentum profits are related to changes in systematic risk over-time or to systematically biased investor expectations by studying time-varying systematic risk adjusted returns in the context of the CAPM theory. To perform this analysis, we estimate time-varying betas of portfolios based on a Dynamic Conditional Correlation model (Engle and

Sheppard, 2001) using a new dataset for Brazil, Chile, Mexico and Latin America for the period 2000–2018. Emerging markets have been studied mainly because they present unique characteristics. They are regarded as being more volatile than developed markets (Aggarwal et al.,1999) which is interesting when time-varying approaches for volatility, correlation or other metrics are used. Also, as noted by Harvey et. (2016), as empirical results have a risk of data mining, results may be the consequence of researchers using the same dataset to make papers publishable. Additionally, there is evidence that regions may not behave similarly when contrarian and momentum strategies are analyzed. As an example, Fama and French (2012) found strong momentum returns in North America, Europe and Asia Pacific but not in Japan, meaning that evidence extrapolation may not be always possible even when a market is considered representative. Therefore, it is important to test phenomena that have proved to be interesting using new datasets (Clare and Thomas,1995) and to augment the evidence for non-developed markets.

When we examined our results, we found that there are predictable patterns in momentum and contrarian strategies as they are profitable in different holding periods when past returns are employed to construct simple strategies. However, when evaluating abnormal returns using a CAPM with time varying betas, we did not find evidence that suggests that these returns are related to inefficiencies of the market. The returns adjusted by time-varying systematic risk are not economically and statistically significant in any case considered. A direct implication of this is that portfolio or strategy evaluation in stock markets should incorporate time-varying betas to avoid biases in the estimation of risk exposure and/or risk performance.

The rest of the article is organized as follows: Section 2 revisits the role of risk and states the hypothesis. Section 3 set outs the data and methodology to be used in contrarian and momentum strategies and the specification of DCC model for obtaining time-varying betas. Section 4 presents and discusses the data and the empirical results. Section 5 concludes.

2 Role of risk

Finance research has found that there are some "anomalies" in markets, in which some strategies earn returns that are far from those justified by the systematic risk (Shleifer and Vishny, 1997). The efficient market hypothesis indicates that these abnormal returns must be a compensation for risk and the evidence of significant abnormal returns are product of a misspecified asset pricing model (Fama, 1991). The role of risk presents inconsistencies in the empirical literature, most notably about whether it changes over time, changing the equilibrium of returns (Chan, 1988; Ball and Kothari, 1989; Zarowin,1989). The implication is a change over time of inputs and parameters of assets pricing models, which are usually estimated on static or rolling windows.

When returns are analyzed, the empirical literature has studied the cross section of returns by using the CAPM. The CAPM is a single factor model that decomposes the portfolio or stock expected returns into systematic and idiosyncratic risk, and states that beta is the only risk factor that is important for investors (Andersen, et al., 2006). This model incorporates changes in interest rates, inflation, recessions and other shifts in the economy in the systematic part and unique events that affect the stock individually (e.g. CEO decisions) in the idiosyncratic part. Beta is a parameter that reflects information about the risk of a stock, and it is used in portfolio risk management, portfolio asset selection and allocation and as measure of performance (e.g. Treynor ratio). However, the estimation of beta is performed under the assumption that it remains constant over time, and there is a large literature that states that beta risk is not constant (Jagannathan and Wang, 1996; Brooks et al., 1998; Faff et al., 2000; Andersen et al., 2006).

Campbell et al. (1997) noted that it is in detriment of the CAPM to use a static approach instead of a conditional CAPM with time-varying betas, because expected returns vary over business cycle. Also, the efficient market hypothesis allows the equilibrium rate of return to vary over time, for example Campbell and Cochrane (1999) argue that when the economy is strong investors become more tolerant to risk. Therefore, as there are shifts in investor behavior over time, they should be incorporated in the asset pricing models by including dynamic parameters.

For momentum strategies, Jegadeesh (1990) points out that predictability in stock returns may be due to market inefficiency or changes in systematic risk, as the models used to consider changes in expected returns in time do not allow the variation of risk premia in a more general form. Chan (1988) studies contrarian returns and finds that these returns are linked to time-varying risk. However, the literature presented above has ignored the fact that beta changes over time when considering portfolio risk-adjusted returns.

From the reviewed evidence on explanations from behavioral and traditional approaches of contrarian and momentum strategies, we conclude that there is a misspecification in the tests of CAPM, because beta risk changes continuously as information arrives to the market and therefore risk-adjusted returns should be readjusted to avoid potential biases. Thus, this study uses a time-varying beta for each period, so it differs from the traditional CAPM with a static or rolling-window beta for explaining returns of both strategies.

In light of the evidence the following hypothesis are tested. We begin by proving the existence of the profitability in Latin America of both strategies.

> H_1: *Contrarian and momentum strategies are profitable in Latin American stock markets.*

By testing this hypothesis, we look for predictable patterns in stock returns (in the short and long term). Also, it would imply that prices do not follow random walks. The idea of prices following random patterns may be traced to 1900, when Bachelier (1900) stated that past and present, and even discounted events, are reflected in market prices, thus prices should reflect all available information and be indeed random. In a famous article, Fama (1965) presents evidence that past information of stock returns is useless to predict future movements. The assumption of prices following random walks is violated when past returns let an investor construct a simple strategy to earn abnormal profits. This is tested in contrarian and momentum strategies where only past returns are the only input to create a portfolio that searches to earn positive returns and then we move to the source of these profits.

Our second hypothesis is the following:

> *H*2: *Momentum strategies are related to delay effects.*

As described above, momentum strategies may depend on delay effects, specifically to firm specific information or even to common factors. Jegadeesh and Titman(1993) conclude that momentum profits are "consistent with delayed price reactions to firm-specific information", but they cannot be attributed to lead-lag effects from common factors as in Lo and MacKinlay (1990). Daniel et al. (1998) propose a theory in which momentum is possible because the market initially overreacts to initial news and when latter news arrives they amplify the initial signal. Importantly, for the Emerging countries considered we study if there may be an explanation of the momentum strategies in response to delay effects. However, the different sources of these effects are not considered here separately, instead we limit the analysis by exploring the presence of delay effects in aggregate without distinction.

Our third hypothesis is the following:

> *H*3: *Contrarian and momentum returns are related to time–varying systematic risk.*

Our final hypothesis tests whether changes captured by the time–varying beta in the CAPM context may incorporate abnormal returns in both strategies. This hypothesis is the focus of this study, as the literature considers that systematic risk is not constant over time. Thus, risk adjusted returns may be biased when static estimations are driven to conclude that abnormal returns can be achieved using certain strategies, leading wrongly to a conclusion of market inefficiency. Rejection of this hypothesis would suggest that the alternative explanation of behavioral biases among investors could be the source of this profits.

As found in Lakonishok et al.(1994) contrarian profits may be actually due to extrapolation and not because there are intrinsically riskier. Extrapolation means that investors are excessively optimistic about growth stocks and excessively pessimistic about value stocks, based on past information about this sort of stocks. This implies that investors make mistakes systematically when expectations about future returns are formed. Then, overreaction may be present in stock markets as the information is extrapolated too far in time as noted firstly by De Bondt and Thaler (1985).

Momentum profits may be the result of underreaction, where slow diffusion of information may come from different behavioral biases. Particularly, conservativeness and anchoring biases (Barberis et al., 1998) or the disposition effect, where winner stocks are sold to early and loser stocks hold for too long (Frazzini, 2006). Moskowitz et al. (2012) find that momentum is consistent with the underreaction hypothesis, as there are price reversals in long periods of holding winners (losers), as they become losers (winners), but in the short term these returns are positive.

3 Data and Methodology

We use monthly returns for listed and delisted ordinary stocks for Brazil (1123), Chile (512) and Mexico (710) all in local currency. We also consider Latin America (2345) by merging the stocks of these three countries. Table I summarizes the average number of companies by year in each region. According to the Bloomberg market capitalization index these countries are in the top 10 largest countries by market capitalization in the emerging world in 2018. They are also, the three first larger financial markets of Latin America, representing 85% of total market capitalization. For market proxies we use a S&P/IFCI index[3] for every country. The data source is Eikon Reuters Datastream database from February 2000 till December 2018. The risk-free interest rate proxy is the deposit interest rate available in World Bank databases.

Asset selection in both strategies requires identifying the stocks with the highest and lowest yields for each formation period, the 10th and 1st percentiles are used for this purpose. We follow the J-month/K-month strategy of Jegadeesh and Titman (1993) which is as follows: Stocks are sorted in ascending order based on their past J monthly returns. Equally weighted portfolios are formed for top and bottom deciles to form "winners" and "losers" portfolios respectively. The portfolios have a holding period of K periods. Momentum strategy buys winning portfolios and sells losing portfolios for J = 3, 6, 9, 12 and hold for K = 3, 6, 9, 12 periods, then there are 16 strategies. In contrarian strategy J = 24, 36, 48, 60 and are hold for J = 24, 36, 48, 60, thus there are 16 strategies. In this case, if there are momentum (contrarian) profits the difference between "winners" minus "losers" average cumulative returns show a positive (negative) sign in its K holding period. These zero–cost portfolios are constructed for the 32 strategies described above to test the first hypothesis.

[3] These indices are constructed by Standard & Poor's and are designed to be a liquid and investable benchmark portfolio.

In momentum strategies a second set of strategies is calculated by skipping one month between the portfolio formation period and holding period. By doing this the some microstructure issues are reduced, as lead–lag effect, bid–ask spread and price pressure are reduced (Jegadeesh,1990; Lo and MacKinlay,1990; Lehmann,1990). For robustness and to increase the power of tests, overlapping portfolios are considered in all holding periods. For example, in strategy J = 3 and K = 3 portfolio formation begins in time t+0 and end in t+3 where the holding period begins until t+6. At the same time, a portfolio with formation period between t+1 and t+4 is considered and therefore its holding period is t+4 to t+7, and so on for the rest of the available periods.

We exclude stocks with low liquidity based on the 5% smallest market capitalization. This controls to some degree the fact that profits in contrarian and momentum strategies may be driven by the presence of small stocks (Zarowin,1989; Rouwenhorst,1998; Jegadeesh and Titman,2001). We also dropped companies in the financial and utilities sectors.

To estimate the time-varying systematic risk, we estimate the CAPM with a time-varying beta. To estimate this dynamic beta, we use a M-GARCH class model. Time–varying correlation and variance have been estimated from DCC models in financial literature in the estimation of hedge ratios, optimal weights for portfolio allocation and spillover effects (Bollerslev et al., 1988; Chang et al., 2011). Then, we follow Engle and Sheppard (2001) where the theoretical and empirical properties of DCC models are developed. The capacity of the DCC in high dimensional contexts overcomes some of the limitations of BEKK models (named after Baba, Engle, Kraft and Kroner in 1990), especially the high number of parameters to be estimated and the possibility of non-convergence, which are inconvenient in practice. The DCC model captures several of the stylized facts of the financial time series like correlation clustering (similar to the volatility clustering). This correlation is more likely to be high at moment t, if it was high at moment t-1, so that if there is a shock in the correlation in this period, the effect will also have an impact in the next period. In the estimation we use a skewed t distribution of error for modeling returns, which is a more realistic approach to describe stock returns because of heavy tails and negative asymmetry (see appendix A for DCC model specification used in this study).

Following the procedure describe in appendix A, a bivariate estimation of DCC model is driven between the benchmark portfolio and the equally weighted portfolio given by a momentum or contrarian strategy. From this estimation it is possible to obtain, in every point of time, the conditional variance and co–variances of returns. Then the time-varying beta is estimated as follows:

$$\beta_{it} = \frac{\mathrm{cov}(\mathrm{r_{it}}, \mathrm{r_{bt}})}{\mathrm{var}(\mathrm{r_{bt}})} \tag{1}$$

Where β_{it} is the beta of portfolio i at time t, $\mathrm{cov}(r_{it})$ is the conditional covariance between portfolio i and its benchmark at time t while $\mathrm{var}(r_{bt})$ is the conditional variance of the benchmark portfolio.

Note that in the context of CAPM we estimate the time-varying beta and obtain an alpha for every holding period and for every portfolio without the estimation by ordinary least squares or other type of model. As we have proxies for market and risk-free returns and the parameter beta for every point of time, we can obtain alpha alone from CAPM equation. Additionally, in this case a non-overlapping approach is driven using only strategies J = 3 and K = 12, and, J = 24 and K = 60 for momentum and contrarian returns respectively. Then, we replace beta from equation (1) in equation (2) the CAPM specification, so that:

$$r_{it} - r_{ft} = \alpha_{it} + \beta_{it}\left(r_{bt} - r_{ft}\right) + \varepsilon_{it} \tag{2}$$

$$\mathbb{E}(\varepsilon_{it}) = 0$$

$$\mathbb{E}\left(\varepsilon_{it}, \left(r_{bt} - r_{ft}\right)\right) = 0$$

$$Cov\left(\varepsilon_{it},(r_{bt}-r_{ft})\right)=0, \quad \forall_i$$

$$Cov(\varepsilon_{it},\varepsilon_{it-1})=0, \quad \forall_{i\neq j}$$

Where α_{it} is the abnormal return of the portfolio i at time t gained over the sensitivity of portfolio returns to risk premia, which in this case is its own index from SP/IFCI minus the deposit rate for every country. Note that under this specification, in the CAPM there are no other risk factors that explain portfolio returns and α_{it} should be zero if markets are efficient. Then, to test hypothesis 3 we estimate α_{it} across time for contrarian and momentum portfolios and explore if there are any significant abnormal returns.

4 Results

In this section we first document the portfolio returns for contrarian and momentum strategies described in the last section. Then, we present the time–varying systematic adjusted returns. Robustness of the results is presented at the end of this section. All tables are presented at the end of the paper.

4.1 Momentum strategies

Tables II, III, IV and V report the average cumulative returns and the t-test for winners (buy), losers (sell) and zero cost portfolios (winners minus losers) for the 32 strategies in momentum described above for Brazil, Chile, Mexico and Latin America respectively. Each table contains two panels. In panel A portfolios are formed immediately after ranking stocks by their J past cumulative returns. In panel B portfolios are formed by skipping one month. If there are delay effects, panel B should not show any significance in cumulative returns compared to panel A for momentum strategies, as the one month skipped should include reversals from the incorporation of new information.

For all four regions considered, past winners are profitable as cumulative returns are statistically significant. The most successful short-term long strategy (K = 3) is found in Mexico with J = 6 and an average cumulative return of 3.74%. The long positions in past winners is quite profitable as t-test are as a high as 9.04 in J = 6/K = 12 in Mexico. On the other hand, panel B of the same tables, shows that when we skip one month between ranking stocks and portfolio formation, all strategies are still statistically significant and cumulative returns hold, in comparison with the non–lagged returns. Thus, delay effects do not appear to explain momentum profits as mentioned before in any country studied. These results are quite similar to those in Jegadeesh and Titman (1993) for U.S market for 1965 to 1989 period.

On the short side of the strategies there is no evidence they are profitable in most cases. These strategies have positive signs for almost all holding periods. However, it is worth noting that when the holding period increases, the cumulative returns of past losers increase in all regions. These suggests that a contrarian effect is under way, as past losers will turn into future winners. In this section, the zero cost portfolios have cumulative returns statistically different from zero. Brazil is the region that exhibits the shortest momentum, as the only formation period, K = 3 is positive and statistically significant. Also note that skipping one month does not change these returns. Therefore, validation of the first hypothesis, on the predictable patterns in Latin America, is found to be strong and delay effects appear to have no explanation as a source of these profits.

4.2 Contrarian strategies

As in the momentum strategies, tables VI, VII, VIII and IX report the average cumulative return and its respective t–test for different formation and holding periods. Here, contrarian strategies will work if past winners become future losers, and past losers become future winners.

Results show that past losers are profitable in the four regions studied.

However, past winners do not exhibit negative returns in the majority of holding periods. In fact, these returns are positive and statistically significant, except for holding periods above the 60 months and formation periods above 48 months, which are negative. As noted, as the holding period increases, cumulative returns tend to decrease until they turn to negative when the holding period is greater than 48 months. As contrarian profits are usually a long- term phenomena, this may be the case for all regions. The results behave in the manner described, except in Mexico, which exhibit no contrarian effect. Mexico is a special case because all cumulative returns, for past winners and past losers, are positive and statistically significant. Then, contrarian strategies are not useful for investors just following past returns in this country. When considering Latin America as a whole, the contrarian effect is less strong, but its profits tend to be greater in past losers as the holding period increases. This may suggests that contrarian profits take longer when compared with results for developed countries (De Bondt and Thaler,1985; Clare and Thomas,1995; Dissanaike,1997; Moskowitz et al. 2012).

Zero cost contrarian strategies hold for any holding period in Brazil and Chile and just for 60 months holding periods in Latin America.

In summary, our evidence suggests that predictable patterns in the short and long term exist in Emerging Markets, then there are priced factors. Particularly, momentum is present in all regions and contrarian profits are present in Brazil, Chile and Latin America. Mexico does not have any trace of contrarian effect, so this country is dropped from contrarian study in next subsection.

4.3 Time-varying systematic adjusted returns

As mentioned above, in this section we focus on long strategies for contrarian and momentum investment. They are the ones that proved to be profitable and are investable because there are restrictions to short-selling in practice when Emerging

Markets are considered (Van der Hart et al.,2003). Also, these strategies can be compared to our selected market proxies which are also investable portfolios. Moreover, we extend the analysis using daily data in the estimation of DCC models in order to have as much data as possible. Strategies for the longer holding periods are used. That is, momentum strategy J = 3/K = 12, and contrarian strategy J = 24/K = 60 are subject of analysis in order to evaluate whether time variation of systematic risk may explain returns from both strategies in Brazil, Chile and Mexico. These portfolio formations and holding periods are examined in detail and are representative for the results of others[4].

Table X shows the results for momentum. This table is separated by pairs of columns for every country where the first contains the average cumulative raw returns and the second column presents the average cumulative returns adjusted by time-varying systematic risk. This column is the definition of abnormal returns from the CAPM with beta varying over time. Results show two interesting facts. First, when considering raw returns all strategies have statistically significant and positive returns and are quite similar in all regions, averaging 15.89% per year. Second, when considering time-varying systematic adjusted returns, no momentum strategy appears significantly profitable. For example, in Brazil these returns are negative, but its raw returns were 16.16% in average and fell to -3.6% when adjusted. Chile and Mexico, where momentum showed to be strong, have positive adjusted returns but they are not significant. Moving on to contrarian strategies results are presented for Brazil and Chile.

Presented in a similar way, table XI shows contrarian returns of past losers. Results show that raw returns are positive, but when considering systematic adjusted

[4] Jegadeesh and Titman(1993) select J=6 and K=6 as a representative strategy for results. Here we use in both momentum and contrarian strategies the shortest formation period and the longest holding period considered so far to be representative.

returns, contrarian profits turn to negative in both regions. Again, when abnormal returns are adjusted for time-varying systematic risk, profits appear to be nonexistent. To sum up, momentum and contrarian profits results are present in the regions studied. However, abnormal profits vanish when considering changes in the equilibrium of required returns in the CAPM context by letting beta vary over time (Chan, 1988; Ball and Kothari, 1989; Jegadeesh, 1990). This result suggests that ignoring variation of beta can bias risk adjusted returns in strategy or portfolio evaluation.

4.4 Robustness of the results

As we use an asset pricing model to study market efficiency, we need to be aware of the joint hypothesis problem, which states that market efficiency is not testable per se and that an asset pricing model must be used to test it (Fama,1991). If a test of market efficiency suggests that the market is not efficient, this result is never conclusive because an alternative explanation of the results is that our model is incomplete, that we may have a bad model problem and not necessarily that the market is inefficient. This difficulty is faced when academics and practitioners try to measure the fundamental value of an asset, which is not observable. In our case, as we described above, we control by size effects, market microstructure, survivorship bias, and delay effects but not by the bad model problem. To deal with this issue, in this section we present a robust test of efficiency that follows the work of Lakonishok et al.(1994) who implement a test that does not require the use of an asset pricing model. The test is based in the following observation: Investors are less risk tolerant when the economy is weak, because their utility is determined by their level of consumption considered relative to its past (Campbell and Cochrane, 1999). Then, if contrarian and momentum strategies are riskier, they should underperform the market in bad states of the world when marginal utility of wealth is high and both strategies will be avoided by risk-averse investors. This is a very simple way to test if a strategy is riskier according to a rational maximization agent approach. To study this, we calculate 25% of the worst annual GDP growth for Brazil, Chile and Mexico. After that, we calculate overlapping portfolios for momentum and contrarian strategies to compare them to a market proxy portfolio in those periods of economic drawdowns. The comparison takes place in every month of the worst GDP growth year, where we observe if cumulative returns of every strategy are greater than the market proxy in these extreme down markets and economics recessions. If momentum or contrarian strategies outperform the market portfolio it cannot be concluded that one strategy is riskier because investor's marginal utility is higher compared to other states of the world.

Table XII presents the performance of momentum portfolios in the lower 25% of the recorded GDP growths in each country, the average cumulative return and the difference between momentum portfolios and market portfolio and its t-test. The results show that momentum strategies performed at least as well as the market in Brazil, Chile and Mexico. While differences in performance is positive in Chile and Mexico, it is negative in Brazil, but not statistically significant in any case. Thus, in extreme down markets momentum portfolios do not appear to underperform the market, which is a signal that these strategies are not riskier. These results are contrary to those found above when time-varying systematic risk is considered to adjust returns by risk. This suggests that holding momentum portfolios for the long-term implies assuming more risk, but for short-term holdings in declining markets, this is not necessarily the case. In addition, it is known that momentum is one factor that usually performs better than the market in recessions in developed markets, and evidence here suggests that emerging markets might not be an exception as they have the same performance in recessions, but further investigation should be needed in order to clarify this issue.

For contrarian strategies table XIII presents performance in the same manner as in momentum. In Brazil and Chile there are positive returns but are lower than their market proxies. Thus, contrarian portfolios have more downside risk in down markets, as this difference is negative and statistically significant. Contrarian or value factor is associated with excess of returns in upside markets rather than downside ones in developed markets. Results suggests that this is the case for the two emerging countries studied, showing that value strategies are riskier than the market portfolio proxy in extreme down markets.

To summarize, the analysis suggests that the conclusion of market inefficiency obtained from strategies studied here, even in down markets, does not show that abnormal returns can be earned without assuming more risk, given the change of systematic risk over time. On the one hand, no evidence of overreaction in the case of contrarian strategies appear to be an explanation of this returns, and systematic risk adjusted returns show that this strategy is profitable because investors assume more risk, even in recessions. On the other hand, momentum has mixed results. When systematic risk adjusted returns are incorporated, there is no excess of returns. In this sense, momentum returns are a product of assuming more risk. However, in down markets this strategy has performed at least as well as the market portfolio proxy, suggesting that momentum is as risky as the market portfolio. Thus, investors will keep these stocks in their portfolios because their wealth will not be affected more by momentum than by the market portfolio. Also, when considering other sources of momentum returns as delay effects for common factors and idiosyncratic specific information, we found no evidence of this effect to explain this anomaly.

5 Conclusions

In this study we confirmed that there exist predictable patterns in stocks markets in Emerging Markets and significant profits from two simple applications of contrarian and momentum strategies. The profits of these strategies seem to be related to time-varying systematic risk. Our results imply that risk adjusted returns may be biased if systematic risk in time is not incorporated. In addition, evidence against investors not being fully rational, as behavioral approach states, is not found when strategies' abnormal returns are defined by alpha in the CAPM with beta varying over time. In this sense, these factor returns are a compensation for risk.

Further findings indicate that when considering down markets and recessions, contrarian strategies underperform the markets in Brazil, Chile and Mexico. This makes risk averse investors less likely to have this sort of portfolio, because their wealth will be more negatively affected by holding a value portfolio than by the market portfolio. In momentum strategies there is no evidence that they are riskier, as they perform at least as well as the market when there is downside risk in markets or the economy. Thus, momentum presents some mixed evidence, as it appears to be riskier when systematic risk adjusted returns are considered but at least as riskier as the market in downturns of the economy in all three countries. Results for momentum also show that there is no evidence that they are related to delay effects by common factors or idiosyncratic information. Also, evidence presented here does not allow to distinguish between the presence of one of them separately. Future investigation should include Fama-French risk factors in order to complement the systematic time-varying risk-adjusted returns when it is not possible to describe them just by their exposure to market risk. Finally, the evidence presented here shed light that value and momentum factor returns are a compensation for risk, then the sort of risk that drives returns of these strategies should be of interest of academics and practitioners.

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Appendix A. DCC model specification

This appendix presents details concerning the specification of DCC model in a bivariate environment. To perform the estimation of the dynamic covariance matrix is the DCC model is as follows:

Consider N series of returns and assume they are independent (or serially uncorrelated). Then de ne the white noise vector with zero mean $\epsilon = r_t - \mu$ where r_t is the vector of nx1 of the returns and μ is the expected returns vector. Although the returns do not have autocorrelations, they can be correlated contemporaneously, that is:

$$\sum_t = \mathrm{E}_{t-1}[(rt - \mu)(rt - \mu)']$$

Which may or may not be a diagonal matrix. Moreover, the conditional variance may vary over time, depending on past information.

The DCC model involves two steps, the first consists of obtaining the conditional heteroscedasticity of each series of returns individually, r_t^i. Then, the individual volatility σ_t^i is estimated using a univariate GARCH(1,1) model with asymmetric student's t error distribution. A diagonal matrix, call D_t, with these conditional volatilities is formed, where $D_t^{i,i} = \sigma_t^{i,i}$ and $D_t^{i,i} = 0$ if $i \neq j$. So, the standardized residuals are:

$$v_t = D_t^{-1}(r_t - \mu)$$

note that standardized residuals have unitary conditional volatility. Now, define the matrix:

$$\bar{R} = \frac{1}{T}\sum_{t=1}^{T} v_t {v_t}'$$

and this is the CCC constant conditional correlation estimator.

The second step is to generalize Bollerslev's CCC model to capture correlation dynamics, hence the name DCC conditional dynamic correlation model. The correlations of the DCC model are:

$$Q_t = \bar{R} + \alpha(v_{t-1}v'_{t-1} - \bar{R}) + \beta(Q_{t-1} - \bar{R})$$

Where $Q_t^{i,j}$ is the correlation between the series of returns r^i and the series r^j at time t. This specification is a DCC(1,1), which can be generalized, however for purposes of this paper it follows that this order serves as a good measure of dynamic correlations. Here it is possible to obtain a matrix of conditional variances and covariances, which are in turn use to estimate beta in the CAPM in a time-varying fashion.

Note that the DCC(1,1) has the functional form of a univariate GARCH(1,1), however, instead of estimating 3 parameters, $2 + \frac{n+1}{2}$ must be estimated, and in order for there to be a stationary correlation it must be met that $\alpha + \beta < 1$, that is, the correlation reverts to the mean and fluctuates around $\overline{R}$, the unconditional correlation.

6 Tables

Table I: Average number of companies per year, country and region

Year	Brazil	Chile	Mexico	Latam
2000	275	153	199	628
2001	285	154	203	643
2002	293	155	205	653
2003	301	157	206	664
2004	306	161	208	674
2005	318	165	211	694
2006	334	170	216	720
2007	369	176	219	763
2008	391	177	224	792
2009	397	179	225	800
2010	408	182	227	817
2011	422	185	233	840
2012	428	191	235	854
2013	434	195	238	867
2014	441	195	241	876
2015	443	196	245	884
2016	446	198	250	894
2017	451	202	254	907
2018	457	204	256	917

Table II. Momentum Strategies Brazil

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

		Panel A					Panel B			
J	K=	3	6	9	12	K=	3	6	9	12
3	Winner	2.47***	3.55***	5.30***	7.17***		1.82**	3.07***	4.98***	6.84***
		(3.3)	(3.03)	(3.5)	(4.01)		(2.46)	(2.64)	(3.35)	(3.86)
3	Loser	0.75	1.70	1.61	2.22		0.41	1.58	1.16	2.30
		(0.82)	(1.12)	(0.8)	(0.93)		(0.45)	(1.03)	(0.58)	(0.97)
3	Winner-Loser	1.72***	1.85*	3.67***	4.95***		1.82**	1.49	3.81***	4.54***

		(2.94)	(1.91)	(2.97)	(3.62)	(2.22)	(1.50)	(3.05)	(3.27)
6	Winner	1.39**	2.71**	4.52***	6.21***	1.09	2.44**	4.30***	5.78***
		(1.99)	(2.47)	(3.16)	(3.81)	(1.58)	(2.22)	(3.05)	(3.58)
6	Loser	1.05	1.56	1.78	3.1	1.12	1.68	1.89	3.55
		(1.03)	(0.94)	(0.83)	(1.23)	(1.12)	(1.01)	(0.89)	(1.44)
6	Winner-Loser	0.34	1.15	2.74*	3.12*	-0.02	0.77	2.41	2.23
		(0.44)	(0.94)	(1.78)	(1.75)	(-0.02)	(0.63)	(1.58)	(1.27)
9	Winner	1.69**	3.01***	4.89***	6.43***	1.53**	3.15***	4.79***	6.31***
		(2.43)	(2.7)	(3.5)	(3.99)	(2.19)	(2.88)	(3.52)	(3.94)
9	Loser	1.11	1.87	2.67	4.26	0.86	1.65	2.61	4.02
		(1.06)	(1.07)	(1.19)	(1.63)	(0.81)	(0.96)	(1.17)	(1.57)
9	Winner-Loser	0.57	1.14	2.21	2.17	0.68	1.50	2.18	2.29
		(0.72)	(0.89)	(1.34)	(1.11)	(0.85)	(1.17)	(1.32)	(1.19)
12	Winner	1.52**	3.20***	4.71***	5.74***	1.55**	3.12***	4.59***	5.42***
		(2.30)	(3.12)	(3.63)	(3.69)	(2.42)	(3.11)	(3.56)	(3.50)
12	Loser	1.05	2.22	3.28	4.49*	1.22	2.37	3.33	4.77*
		(0.99)	(1.29)	(1.49)	(1.75)	(1.19)	(1.41)	(1.56)	(1.90)
12	Winner-Loser	0.48	0.98	1.43	1.26	0.33	0.75	1.26	0.67
		(0.6)	(0.75)	(0.85)	(0.64)	(0.41)	(0.58)	(0.76)	(0.34)

Note: *p<0.1; **p<0.05; ***p<0.01

Table III. Momentum Strategies Chile

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

			Panel A				Panel B			
J		K=	3	6	9	12	K=	3	6	9	12
3	Winner		2.90***	5.06***	6.95***	8.01***		2.93***	4.87***	5.46***	7.46***

		(5.09)	(5.25)	(5.62)	(5.35)	(4.88)	(4.96)	(5.21)	(4.90)
3	Loser	-0.72	-0.38	0.15	2.02	0.48	0.01	0.86	2.86*
		(-1.14)	(-0.39)	(0.11)	(1.30)	(-0.76)	(0.01)	(0.66)	(1.85)
3	Winner-Loser	3.62***	5.02***	6.48***	5.99***	3.41***	4.85***	5.61***	4.61***
		(6.74)	(6.35)	(6.48)	(4.91)	(6.08)	(5.68)	(5.34)	(3.91)
6	Winner	3.06***	5.34***	7.13***	8.28***	2.76***	4.71***	6.63***	7.34***
		(4.83)	(5.32)	(5.53)	(5.29)	(4.19)	(4.82)	(4.89)	(4.64)
6	Loser	-0.35	0.15	1.86	3.75**	-0.03	0.75	2.56**	4.37***
		(-0.54)	-0.14	(1.42)	(2.47)	(-0.04)	(0.74)	(1.99)	(2.86)
6	Winner-Loser	3.42***	5.19***	5.27***	4.53***	2.79***	3.96***	3.80***	2.97**
		(5.74)	(5.9)	(4.95)	(3.77)	(4.46)	(4.54)	(3.54)	(2.45)
9	Winner	2.85***	4.65***	6.27***	7.36***	2.43***	3.99***	5.45***	6.51***
		(4.65)	(4.9)	(4.88)	(4.67)	(4.09)	(4.14)	(4.20)	(4.11)
9	Loser	-0.07	1.03	2.61**	4.76***	0.20	1.52	3.19**	5.37***
		(-0.09)	(0.95)	(1.98)	(2.95)	(0.28)	(1.44)	(2.44)	(3.25)
9	Winner-Loser	2.91***	3.62***	3.66***	2.60***	2.23***	2.47***	2.26**	1.15
		(4.58)	(4.10)	(3.52)	(2.10)	(3.60)	(2.87)	(2.19)	(0.91)
12	Winner	2.37***	4.26***	5.94***	7.08***	2.23***	3.74***	5.25***	6.37***
		(4.03)	(4.41)	(4.71)	(4.54)	(3.60)	(3.82)	(4.05)	(4.05)
12	Loser	0.40	1.66	3.66***	6.02***	0.82	2.22**	4.36***	6.58***
		(0.57)	(1.63)	(2.75)	(3.65)	(1.22)	(2.20)	(3.25)	(3.92)
12	Winner-Loser	1.97***	2.60***	2.28**	1.06	1.41**	1.52*	0.88	-0.21
		(3.05)	(2.84)	(2.21)	(0.87)	(2.21)	(1.68)	(0.85)	(-0.17)

Note: *p<0.1; **p<0.05; ***p<0.01

Table IV. Momentum Strategies Mexico

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

		Panel A					Panel B			
J		K= 3	6	9	12	K=	3	6	9	12
3	Winner	3.46***	6.20***	8.66***	11.09***		3.18***	5.74***	8.27***	10.60***
		(5.63)	(6.33)	(6.98)	(7.83)		(5.08)	(5.79)	(6.69)	(7.50)
3	Loser	-0.08	0.78	2.47	4.47**		0.40	1.48	3.18**	5.32***
		(-0.10)	(0.64)	(1.61)	(2.45)		(0.56)	(1.25)	(2.03)	(2.88)
3	Winner-Loser	3.53***	5.44***	6.19***	6.61***		2.78***	4.26***	5.09***	5.28***
		(6.30)	(6.80)	(6.04)	(5.68)		(5.33)	(5.53)	(5.01)	(4.54)
6	Winner	3.37***	6.38***	9.04***	11.28***		3.14***	6.09***	8.56***	10.75***
		(5.61)	(7.00)	(7.64)	(8.54)		(5.33)	(6.62)	(7.43)	(8.23)
6	Loser	0.33	1.39	2.78*	4.91**		0.85	1.80	3.32**	5.71***
		(0.43)	(1.14)	(1.73)	(2.59)		(1.14)	(1.43)	(2.01)	(3.03)
6	Winner-Loser	3.04***	4.99***	6.26***	6.37***		2.29***	4.28***	5.24***	5.03***
		(4.70)	(5.38)	(5.20)	(4.59)		(3.78)	(4.66)	(4.43)	(3.77)
9	Winner	3.28***	6.38***	8.73***	10.87***		3.16***	6.02***	8.16***	10.34***
		(5.73)	(7.26)	(7.96)	(8.27)		(5.47)	(6.87)	(7.48)	(7.80)
9	Loser	0.38	1.11	2.52	5.03***		0.47	1.32	3.08*	5.94***
		(0.48)	(0.85)	(1.54)	(2.81)		(0.61)	(1.02)	(1.91)	(3.42)
9	Winner-Loser	2.89***	5.27***	6.21***	5.84***		2.69***	4.70***	5.07***	4.40***
		(4.49)	(5.18)	(4.95)	(4.09)		(4.38)	(4.72)	(4.15)	(3.21)
12	Winner	3.09***	5.74***	8.11***	10.41***		2.96***	5.44***	7.82***	9.78***
		(5.45)	(6.60)	(7.14)	(7.50)		(5.32)	(6.14)	(6.74)	(6.97)
12	Loser	0.30	1.59	3.71**	6.75***		0.47	2.05	4.56***	7.87***
		(0.37)	(1.20)	(2.30)	(4.05)		(0.61)	(1.58)	(2.94)	(5.01)
12	Winner-Loser	2.79***	4.15***	4.39***	3.66***		2.49***	3.39***	3.26***	1.91
		(4.16)	(4.00)	(3.53)	(2.66)		(3.90)	(3.41)	(2.73)	(1.45)

Note: *p<0.1; **p<0.05; ***p<0.01

Table V. Momentum Strategies Latam

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

		Panel A					Panel B			
J	K=	3	6	9	12	K=	3	6	9	12
3	Winner	1.94**	2.57*	3.81**	4.90**		1.58*	2.16	3.37*	4.54**
		(2.02)	(1.72)	(2.06)	(2.28)		(1.66)	(1.47)	(1.86)	(2.12)
3	Loser	-0.67	-0.73	-0.94	-0.63		-0.65	-0.41	-0.75	-0.33
		(-0.65)	(-0.43)	(-0.42)	(-0.23)		(-0.63)	(-0.23)	(-0.32)	(-0.12)
3	Winner-Loser	2.60***	3.30***	4.75***	5.53***		2.24***	2.56***	4.12***	4.87***
		(4.70)	(3.74)	(4.02)	(4.04)		(3.92)	(2.77)	(3.34)	(3.52)
6	Winner	1.41	2.39*	3.68**	4.84**		1.12	2.08	3.43*	4.53**
		(1.53)	(1.66)	(2.06)	(2.33)		(1.23)	(1.46)	(1.93)	(2.17)
6	Loser	-0.37	-0.31	-0.32	0.54		0.02	0.09	0.12	1.14
		(-0.33)	(-0.17)	(-0.13)	-0.19		(0.02)	(0.05)	(0.05)	(0.41)
6	Winner-Loser	1.78**	2.70**	3.99***	4.30**		1.10	1.99*	3.31**	3.39**
		(2.57)	(2.37)	(2.74)	(2.52)		(1.62)	(1.74)	(2.27)	(2.02)
9	Winner	1.28	2.35*	3.61**	5.03**		1.14	2.34*	3.48**	4.89**
		(1.43)	(1.68)	(2.04)	(2.44)		(1.26)	(1.67)	(1.96)	(2.34)
9	Loser	-0.17	-0.16	0.41	1.49		-0.24	-0.01	0.64	1.62
		(-0.14)	(-0.08)	(0.16)	(0.52)		(-0.21)	(-0.01)	(0.25)	(0.57)
9	Winner-Loser	1.45**	2.51**	3.20**	3.54**		1.39**	2.36**	2.84*	3.28*
		(2.08)	(2.16)	(2.14)	(2.04)		(2.01)	(2.05)	(1.90)	(1.94)

12	Winner	1.07	2.10	3.24*	4.18**	1.22	2.05	3.08*	4.00*
		(1.22)	(1.51)	(1.84)	(2.00)	(1.37)	(1.46)	(1.73)	(1.90)
12	Loser	0.25	0.18	1.00	2.03	-0.06	0.62	1.37	2.59
		(-0.21)	(0.09)	(0.40)	(0.72)	(-0.05)	(0.31)	(0.56)	(0.94)
12	Winner-Loser	1.33*	1.92*	2.25	2.15	1.29*	1.43	1.71	1.41
		(1.88)	(1.63)	(1.47)	(1.20)	(1.84)	(1.24)	(1.12)	(0.81)

Note: *p<0.1; **p<0.05; ***p<0.01

Table VI. Contrarian Strategies Brazil

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

J	K=	24	36	48	60
24	Winner	8.31***	10.82***	12.95***	12.20***
		(3.60)	(3.58)	(3.05)	(2.46)
24	Loser	16.07***	21.46***	27.73***	34.93***
		(3.99)	(4.13)	(4.62)	(5.21)
24	Winner-Loser	-7.76**	-10.64***	-14.77***	-22.74***
		(-2.56)	(-3.24)	(-3.84)	(-5.20)
36	Winner	6.88***	8.87***	8.31**	5.72
		(2.96)	(2.88)	(2.01)	(1.24)
36	Loser	12.82***	16.84***	18.77****	21.90***
		(2.91)	(2.99)	(2.85)	(3.08)
36	Winner-Loser	-5.95*	-7.96**	-10.46***	-16.19***
		(-1.89)	(-2.31)	(-2.80)	(-3.93)
48	Winner	3.98	4.78	1.48	-0.07
		(1.59)	(1.54)	(0.41)	(-0.01)
48	Loser	13.19***	12.96**	9.69*	17.58***
		(3.04)	(2.47)	(1.70)	(2.81)
48	Winner-Loser	-9.21***	-8.17***	-8.21**	-17.65***
		(-3.14)	(-2.71)	(-2.35)	(-4.91)
60	Winner	0.33	-2.43	-4.85	-8.13**
		(0.14)	(-1.00)	(-1.57)	(-2.11)
60	Loser	9.68**	4.62	4.01	12.69**

		(2.36)	(1.07)	(0.86)	(2.35)
60	Winner-Loser	-9.34***	-7.05**	-8.87***	-20.82***
		(-3.41)	(-2.50)	(-2.82)	(-6.00)

Note: *p<0.1; **p<0.05; ***p<0.01

Table VII. Contrarian Strategies Chile

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

J	K=	24	36	48	60
24	Winner	10.50***	11.26***	11.68***	10.73***
		(6.29)	(5.61)	(4.52)	(3.98)
24	Loser	15.41***	18.40***	18.34***	16.45***
		(4.94)	(5.57)	(5.37)	(4.26)
24	Winner-Loser	-4.92**	-7.14***	-6.66**	-5.71*
		(-2.28)	(-2.86)	(-2.41)	(-1.75)
36	Winner	5.99***	5.43***	4.75**	2.13
		(3.97)	(3.06)	(2.02)	(1.05)
36	Loser	14.18***	14.71***	11.58***	5.38*
		(4.80)	(5.09)	(3.70)	(1.74)
36	Winner-Loser	-8.19***	-9.27***	-6.83**	-3.25
		(-3.53)	(-4.05)	(-2.53)	(-1.15)
48	Winner	1.48	1.86	-1.96	-4.78***
		(1.15)	(1.25)	(-1.02)	(-2.47)
48	Loser	11.97***	11.47***	5.32**	1.11
		(4.52)	(4.28)	(2.28)	(0.54)
48	Winner-Loser	-10.49***	-9.61***	-7.29***	-5.89***
		(-4.67)	(-4.13)	(-3.05)	(-2.76)
60	Winner	0.35	-2.35*	-8.46***	-12.29***
		(0.23)	(-1.72)	(-4.10)	(-5.81)
60	Loser	8.49***	2.59	-3.15	-2.96
		(3.12)	(1.03)	(-1.42)	(-1.40)

60	Winner-Loser	-8.14***	-4.95**	-5.31***	-9.33***
		(-3.61)	(-2.41)	(-2.62)	(-4.54)

Note: *p<0.1; **p<0.05; ***p<0.01

Table VIII. Contrarian Strategies Mexico

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

J	K=	24	36	48	60
24	Winner	27.39***	41.77***	49.62***	55.44***
		(11.94)	(16.30)	(18.81)	(21.67)
24	Loser	15.92***	20.27***	31.02***	41.55***
		(8.49)	(9.04)	(9.38)	(10.25)
24	Winner-Loser	11.47***	21.50***	18.60***	13.89***
		(4.46)	(8.16)	(6.71)	(3.87)
36	Winner	27.74***	38.19***	43.69***	47.10***
		(11.90)	(15.54)	(17.80)	(19.52)
36	Loser	13.31***	18.95***	28.86***	35.65***
		(7.04)	(8.42)	(8.58)	(8.81)
36	Winner-Loser	14.43***	19.24***	14.83***	11.45***
		(5.50)	(7.74)	(4.52)	(2.78)
48	Winner	21.11***	29.26***	32.70***	36.55***
		(8.51)	(11.77)	(14.57)	(14.87)
48	Loser	11.09***	15.03***	20.66***	27.83***
		(8.14)	(8.32)	(8.11)	(10.19)
48	Winner-Loser	10.02***	14.22***	12.04***	8.72***
		(4.68)	(7.16)	(4.97)	(2.66)
60	Winner	14.87***	20.35***	23.63***	29.62***
		(6.18)	(10.11)	(13.18)	(12.40)
60	Loser	10.42***	9.96***	12.97***	20.84***
		(7.38)	(5.84)	(7.55)	(9.60)
60	Winner-Loser	4.45**	10.40***	10.66***	8.78***

		(2.30)	(6.43)	(4.61)	(3.22)

Note: *p<0.1; **p<0.05; ***p<0.01

Table IX. Contrarian Strategies Latin America

This table presents the results from J/K strategies for overlapping portfolios. Portfolios are ranked based on its J past months cumulative returns in ascending order and equally portfolios are formed with stocks in the first decile and tenth decile to construct winner and past portfolios respectively. The arbitrage portfolio is constructed with the difference between winners and losers. These portfolios are hold for K months and the average of cumulative returns are presented in this table. Panel A presents the average cumulative returns of portfolios formed immediately after the ranking and panel B by skipping one month. t-test are reported in parenthesis. The time frame is February 2000 to December 2018.

J	K=	24	36	48	60
24	Winner	13.89***	19.45***	21.90***	22.67***
		(7.58)	(8.70)	(7.22)	(6.63)
24	Loser	12.91***	16.43***	23.03***	29.42***
		(4.53)	(5.01)	(5.92)	(6.88)
24	Winner-Loser	0.10	3.02	-1.13	-6.76***
		(0.45)	(1.36)	(-0.46)	(-2.68)
36	Winner	12.38***	15.97***	17.35***	16.21***
		(7.18)	(7.53)	(6.16)	(5.86)
36	Loser	10.88***	13.55***	16.93***	19.02***
		(3.76)	(4.06)	(4.49)	(4.84)
36	Winner-Loser	1.50	2.42	0.42	-2.81
		(0.65)	(1.11)	(0.20)	(-1.41)
48	Winner	8.14***	11.17***	9.24***	-12.24**
		(4.54)	(5.48)	(3.70)	(-2.32)
48	Loser	9.59***	9.47***	4.94***	-3.49
		(3.62)	(3.38)	(4.95)	(-0.74)
48	Winner-Loser	-1.44	1.70	-4.16***	-8.75***
		(-0.66)	(0.98)	(-2.82)	(-3.01)
60	Winner	3.95**	3.85***	2.58	2.08
		(2.25)	(2.93)	(1.47)	(0.94)
60	Loser	6.89***	3.20	3.49**	9.26***
		(2.77)	(1.38)	(1.97)	(4.25)
60	Winner-Loser	-2.94	0.65	-0.91	-7.18***
		(-1.42)	(0.40)	(-0.62)	(-5.16)

Note: *p<0.1; **p<0.05; ***p<0.01

Table X. Raw and systematic adjusted returns for momentum profits

This table presents the results of non-overlapping momentum portfolios for J=3/K=12. Results are presented as average cumulative raw returns and average cumulative systematic risk adjusted returns for Brazil, Chile and Mexico for the period 2000 to 2018. T-test are reported in parenthesis.

Brazil		Chile		Mexico	
Raw Returns	Systematic Adjusted	Raw Returns	Systematic Adjusted	Raw Returns	Systematic Adjusted
16.16**	-3.6	15.01**	5.72	16.50**	7.46*
(2.26)	(-0.73)	(2.05)	(0.17)	(2.27)	(1.71)

Note: *p<0.1; **p<0.05; ***p<0.01

Table XI. Raw and systematic adjusted returns for contrarian profits

This table presents the results of overlapping contrarian portfolios for J=24/K=60. Results are presented as average cumulative raw returns and average cumulative systematic risk adjusted returns for Brazil, Chile and Mexico for the period 2000 to 2018. T-test are reported in parenthesis.

Brazil		Chile	
Raw Returns	Systematic Adjusted	Raw Returns	Systematic Adjusted
51.7**	-24.48**	27.53	-10.49
(2.52)	(-2.23)	(1.43)	(-0.94)

Note: *p<0.1; **p<0.05; ***p<0.01

Table XII. Momentum and market profits in down markets

This table presents the results of overlapping momentum portfolios and market proxy returns. Results are presented as the average cumulative returns for momentum and market portfolios for K=3 and J=12. The difference between momentum and market portfolios returns and its t-test in parenthesis. Average GDP of 25% of worst GDP yearly growth between 2000-2018 period.

Country	**Momentum**	**Market**	**Momentum-Market**	**t-test**	**GDP**
Brazil	6.77	9.45	-2.69	(-1.09)	-1.62
Chile	15.36	14.89	0.47	(0.21)	0.79
Mexico	2.67	-0.89	3.56	(1.57)	-0.65

Note: *p<0.1; **p<0.05; ***p<0.01

Table XIII. Contrarian and market profits in down markets

This table presents the results of overlapping contrarian portfolios and market proxy returns. Results are presented as the average cumulative returns for contrarian and market portfolios for K=24 and J=60. The difference between contrarian and market portfolios returns and its t-test in parenthesis. Average GDP of 25% of worst GDP yearly growth between 2000-2018 period.

Country	**Contrarian**	**Market**	**Contrarian-Market**	**t-test**	**GDP**
Brazil	4.63	13.90	-9.28**	(-2.16)	-1.62
Chile	5.83	12.93	-7.11**	(-2.34)	0.79

Note: *p<0.1; **p<0.05; ***p<0.01