On Persistence in Latin American Mutual Fund Performance

by

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Abstract

Persistence in the performance of US mutual funds investing in Latin America is examined using a sample free of survivorship-bias covering the period 2000-2010. Strong evidence of persistence is found, especially more recent years. Overall, Latin American funds performing well (poorly) in any quarter tend to outperform (underperform) the market the following month to a higher degree than what has been documented for US and other emerging market funds. The persisting positive abnormal returns of previously well-performing funds could be a sign of the relative inefficiency in the Latin American equity markets which would offer fund managers more opportunities to exploit market inconsistencies.

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1.0. Introduction

Mutual funds have grown to be one of the largest financial intermediaries in the world, with more than 70,000 funds controlling over $25 trillion worldwide[1] (Investment Company Institute [ICI], 2011). The success of the industry is usually attributed to the low transaction costs and liquidity insurance that professionally managed mutual funds offer investors, alongside their reputation of being able to earn returns superior to comparable benchmark assets. Much of the literature on the mutual fund industry has attempted to explore these attributes and see whether fund managers truly add value for their investors. Do some mutual fund managers possess significant stock-picking ability? And if so, does their ability result in returns that persistently beat the market? These questions are of great interest not only to the academic and financial communities, but also to a wider audience as an increasing number of people consider investing in mutual funds on the belief that mutual funds will provide them with a low-cost medium through which to invest in a diversified portfolio which consistently outperforms the market.[2]

From an academic perspective, examining the existence and persistence in mutual funds' stock-picking and market-timing ability has important implications as to the validity of the efficient market hypothesis. Evidence of persistence in the performance of mutual funds outperforming the market would be in conflict with the efficient market hypothesis in its semi-strong form since it would indicate an exploitation of pricing asymmetries and market anomalies by winning funds (Bollen and Busse, 2005)

Despite the enormous growth in the popularity of mutual funds, research on their performance has generally been sparse. The majority of research to date has been focused on persistence in the performance of US funds, with a handful of studies on EU funds. Even less academic publications focus on mutual funds investing primarily in other regions of the globe. Furthermore, the limited amount of research available that focuses on areas other

[1] 70,358 funds mutual funds with assets amounting to $25.61 trillion as reported at the end of the first quarter of 2011. (ICI 2011)
[2] A surprising 44% of U.S. households have ownership in mutual funds (ICI 2011)

than the United States or European nations tends to examine more general economic subgroups such as emerging markets.

One group of mutual funds that has not been examined specifically is that comprising of funds investing in Latin America. This is surprising considering it is home to a number of lucrative emerging markets such as those of Brazil and Mexico. Latin American markets' volatile, yet fruitful, nature, combined with the increasing globalization of financial markets, has led to a tremendous increase in the number of funds devoted to investing in the region. This growth spurt was set of especially in the late 1980s, during a revival of international lending. Latin America was dubbed the 'darling of Wall Street' (Bollen and Busse, 2005). A global comparison of the growth in Latin American mutual fund assets can be seen in Table 1.

Table 1: Mutual fund assets worldwide in billions of USD

	1996	1999	2002	2005	2007
Latin America	109	148	137	369	723
BRICs	114	131	117	346	1165
USA	3526	6846	6391	8905	12021
Worldwide	6101	11416	11324	17771	26199

Source: Investment Company Institute (ICI), 2011

A closer look at the performance of indexes tracking equity in Latin American markets makes it obvious why Latin American markets are attractive to mutual funds. The Morgan Stanley Capital International, Inc. (MSCI) Emerging Markets (EM) Latin America Index, for instance, has produced astounding (yet very volatile) returns since its inception in 1987. By December 2010, it had gained 9,419,6% in its 23 year existence (with an average annual gain of 21.91%).

A suggested benefit of investing in Latin America is the opportunity for fund managers to find excessively high returns because of the relative inefficiency in the market relative to developed markets (Tkac: 2001). It is therefore expected that mutual funds investing in Latin America will show higher abnormal performance than funds investing in developed markets. Furthermore, it is likely that funds placing large bets in comparably concentrated portfolios, such as one comprising solely of Latin American equity, will display better performance than funds holding more diversified portfolios. This idea is in line with recent strands of literature that find that fund managers that concentrate investments in specific industries perform better, after controlling for risk, than those diversifying investments (Kacperczyk et al.: 2005).

Fund expenses are an important factor to take into consideration. An ‘emerging markets’ classification serves as a good proxy for increased settlement risk and subsequently for mutual funds to charge its clients higher fees. This implies that mutual funds investing in Latin America would have higher costs than funds investing in ‘safer’ markets, resulting in a decrease in the abnormal returns Latin American funds are hypothesized to have relative to funds investing in developed markets (Tkac: 2001).

By adopting a suitable methodology, the aforementioned hypotheses can be tested and compared to results derived from previous studies applying similar theoretical frameworks. This paper will uncover whether mutual funds investing in Latin America show any evidence of performance persistence, whereby persistence is defined as a continued out-or-underperformance.

The remainder of this paper is organized as follows: section 2 provides an overview of dominant publications on the performance persistence of mutual funds, with a focus on recent literature examining funds investing in emerging markets. Section 3 discusses several models used in the measurement of performance persistence. Section 4 outlines the data on mutual funds investing in Latin America. Section 5 will present the findings. Last but not least, section 6 contains concluding remarks and suggestions for further research.

2.0. Literature Review

The extent to which mutual funds persist in their performance has seen a fair amount of attention in both academic and financial journals over the last few decades. The focus, however, has usually been on a select few countries. A range of methodologies have been employed, with some more successful than others. In this section I will provide an overview of the dominant literature available on the subject.

2.1. US Mutual Funds

The vast consensus amongst the majority of research is that performance persistence exists mainly for poorly performing funds. Most of the publications supporting this conclusion do so using evidence from the US mutual fund industry. Grinblatt and Titman (1992) analyze performance persistence in the risk-adjusted returns of 279 US mutual funds during the period 1974 to 1984 and find strong evidence of persistence amongst the worst performing funds. Persistence is not found amongst well-performing funds once transaction costs and management fees are calculated. Hendricks et al. (1993) arrive at a similar conclusion using return data for growth-fixated US funds from 1974 to 1988. Cahart (1997) did extensive research on US mutual funds over the 1963- 1993 period (and founded the Center for Research in Security Prices [CRSP] Survivor-Bias-Free US Mutual Fund Database database while doing so) and determines that although there is no showing of persistence amongst top funds, it is certainly present amongst the poor performers, where it arises from consistently high expenses. An important argument Cahart made in his paper was that most findings of performance persistence (especially amongst well-performing funds) were driven by Jagadeesh and Titman's (1993) momentum effect. According to Cahart, persistent abnormal mutual fund performance is therefore not a result of stock-picking or market-timing ability or a dedicated successful momentum strategy, but instead attributes it to the so-called 'hot hands' phenomena, where fund managers happen by chance to hold relatively larger positions in previously winning stocks. Chen et al (2000) follows a similar line of thought in a study of US mutual funds investing mainly in equity over the years 1975- 1995. Performance persistence is apparent and is also attributed to luck. Volkman and Wohar

(1995) study more than 320 US funds during 1980- 1989 and find persistence in the performance of both winning and losing funds. Wermers (1995) supports a similar idea, finding that funds following momentum strategies realize better performance before management fees and transaction costs. Fletcher (1999) finds contrasting results in his research on 85 American unit trusts over 1985 to 1996. No evidence of persistence is found at all. More recent papers have seen several innovative models such as the Baynesian estimation model for performance evaluation used by Rossi (2008). Huij and Verbeek (2007) examine 6400 US funds from 194 to 2003 using this approach and found that, on average, it is 40% more accurate than using standard OLS alphas. They too conclude that persistence is present solely in poor performers.

2.2. UK Mutual Funds

As far as the UK mutual fund industry is concerned, Quigley and Sinquefield (1999) examine persistence for 752 UK unit trusts on the basis of funds' one-year raw returns. Their research shows similar results to US studies, with poor-performing funds persisting in their performance but well-performing funds not being able to do so. Quigley and Sinquefield (1999) also note that when repeating their analysis for holding periods greater than one year, persistence patterns practically disappear after three years. Evidence from research by Cuthbertson et al. (2005) is in favour of a likewise conclusion. They argue that very few managers genuinely outperform the market, while the persistence in poorly performing funds is linked to poor skill, not bad luck. Upon studying data on 2375 UK mutual funds ranging from 1972 to 1995, Blake and Timmermann (1998) find trends quite different than those found by Quigley and Sinquefield (1999). By forming equally-weighted portfolios of funds based on their two-year historic alphas and evaluating the performance of each portfolio over the following month, they find evidence indicative of persistence of both winning and losing funds over short horizons. Allen and Tan's (1999) work produces the same results, looking at 131 UK investment trusts in the period 1989- 1995 and finding persistence among both top and bottom performers. Fletcher and Forbes (2002), find evidence to the contrary. No persistence in performance is observed using the Carhart measure. A more An interesting study by Lunde et al. (1999) attempts to avoid the aggregation issue by identifying persistence in individual funds through time. They do this by using a contingency table approach with transitional probabilities and ultimately reject the null hypothesis of no persistence.

2.3. International Mutual Funds

Despite most research on mutual fund performance persistence being on either US or UK mutual funds, several papers have shed light on the performance of mutual funds investing in other regions of the world. To my knowledge, there are currently no publications on the performance of mutual funds investing specifically in or from Latin America. There are, however, insightful studies on the mutual fund industries in other regions of the world which reveal some interesting information that could concern the Latin American market as well. Babalos et al. (2005) find persistence in the Greek market for both winning and losing funds only for the 1998-2001 period; any evidence of persistence in the performance of Greek funds disappears thereafter. An explanation for this occurrence is the integration in the international financial system at the beginning of the millennium, leading to an increase in foreign institutional investors and a more competitive fund industry. The result is a more efficient market with less informational asymmetries where funds would struggle to find opportunities to exploit anomalies. Babalos et al. conclude that this phenomenon in the Greek market could be relevant to Latin American and other emerging markets which are also in the gradual process of becoming more integrated internationally.

As far as other countries are concerned, Cortez et al. (1999) concluded that persistence disappears in Portuguese equity funds when using risk-adjusted returns. Vos et al. (1995) finds no predictability in the performance of mutual funds in Australia and New Zealand. Dahlquist et al. (2000) and Christensen (2005) also fail to find any evidence of persistence in mutual fund performance when studying a set of Swedish and Danish equity funds, respectively. Casarin et al. (2002) reports persistence in the risk-adjusted returns of Italian funds, and Deaves (2004) finds the same for funds in Canada. Both, however, conclude that the persistence is limited to short horizons.

Most applicable to the Latin American industry is a recent study by Huij and Post (2011) documenting persistence in the performance of US funds investing in multiple emerging markets over the period 1993 to 2006. Unlike most other research, strong evidence of persistence is found when looking at the return spread between portfolios of well- and poorly- performing funds ranked monthly by their excess returns over the past quarter. The contribution of winning funds is seen to be substantially more significant than in studies on funds from other regions. Since the 'emerging markets' comprise for a substantial part of Latin American markets, a study of funds investing in Latin American markets exclusively is expected to produce similar results. An interesting feat of this study is to determine to what role Latin American mutual funds play in the contribution of winning funds to the persistence in performance noted by Huij and Post (2011).

All in all, the vast array of results found in the studies on performance persistence in mutual funds is an indication of the level of versatility in the measurement methodologies. Small variations in the methods and data used in different studies have produced a wide range of conclusions as to what extent mutual funds persist in performance and how long they do so for. In a later section I will therefore outline the prevailing measurement methodologies in order to clarify their differences.

3.0. Models of Performance Persistence Measurement

Models of performance persistence measurement can be divided into two main categories: contingency table- or rank portfolio- based.

3.1. Contingency Table Approach

The contingency table approach is rather straightforward and will be discussed based on the methodology used by Fletcher and Forbes (2002). According to performance in two consecutive periods, mutual funds are sorted into one of four portfolios: Winners-Winners (WW), Winners-Losers (WL), Losers-Winners (LW), or Losers-Losers (LL). Funds are labeled winners if their market-adjusted return (fund return in excess of the return of the market index) is positive; losers if it is negative. Evidence of persistence arises from a significantly larger number of observations in the WW/LL categories than in the other two. The degree of persistence can be narrowed down to specific timeframes by performing counts on sub periods of the dataset. The strength of the contingency table approach lies in the way in which it tracks the movement of individual funds and assessed their transitional probabilities.

3.2. Rank Portfolio Approach

Among others, Hendricks et al, (1993), Elton et al. (1996), Carhart (1997), and Bollen and Busse (2005) form return-ranked portfolios of mutual funds on varying past period lagged returns and evaluate the performance of the resulting ordered portfolios over a particular future period. A concatenated time series of equally weighted returns is then calculated for each portfolio and the average return for each consequently estimated. For instance, Carhart (1997) forms ten equally-weighted portfolios of mutual funds based on lagged one-year returns on January 1 of each year. Portfolio 1 contains the 10% best performing funds while portfolio 10 contains the 10% worst performing funds. These portfolios are held for one-year during which their return performance is evaluated, and then re-formed on January 1 of the following year. This produces a time series of monthly excess returns (since the return data used is on a monthly basis in excess of the applicable risk-free rate) for each decile portfolio from which the average is taken to provide an overview of each portfolio's performance over the entire (1963-1993) examination period. In short, for every year in Carhart's sample except the last, funds are sorted into ten ranked portfolios by their last one-year excess returns. Over the year following each portfolio's formation, average excess monthly return is calculated and averaged out over the entire sample period. Huij and Post (2011) follow a similar rank portfolio approach for emerging market funds but rank funds monthly based on their performance over the past quarter. Portfolios are ordered by means of terciles instead of deciles since the average number of funds in each period is significantly smaller than in Carhart's (1997) sample. The performance of each tercile is then evaluated in the month following its formation which results in a concatenated time series of monthly, equally-weighted returns for each of the three portfolios. Again, this is used to calculate the average (excess) return for each tercile. Both Carhart (1997) and Huij and Post (2011) subdivide the top and bottom portfolios into thirds for added detail.

The average excess return the concatenated time series produces for each rank portfolio is in itself an acceptable indication of persistence in mutual fund performance. Since persistence is the result of well-performing mutual funds continuing their good performance, and poorly-performing mutual funds continuing their poor performance, persistence would be indicated by descending average excess return values when looking at the portfolio containing the historical best-performers to that containing the worst-performers. The excess average return for each portfolio is a simple return characteristic, however, and does not, by itself, provide much information by which to evaluate performance persistence in relation to any risk factors.

Several measures are used to provide a more in-depth look at relative fund performance. The Sharpe Ratio[3] is a measure of an investment's excess return (relative to the risk-free rate) per unit of volatility. It is, in other words, a reward-to-risk ratio and therefore adjusts returns for risk. The higher the Sharpe ratio, the more preferable the investment is in a risk-averse setting. A negative Sharpe ratio implies a failure to generate more 'return-per-unit-

[3] Computed as $\frac{E(R-R_f)}{\sigma}$, where $E(R-R_f)$ is the expected value of the excess of the fund return (R) over the risk-free rate (R_f), and σ is the standard deviation of the excess return.

of-risk' than the risk-free rate. In the context of evaluating performance persistence using the rank portfolio approach, the Sharpe ratio gives key insight into the portfolio characteristics. For one, it answers the vital question: are the portfolios containing the best-performing funds generating persistently high returns due to the relatively higher levels of risk they are taking? If the Sharpe ratios for the better performing portfolios are significantly lower than those containing the worse performing portfolios, then the answer to the question would be yes, and the existence of persistence in performance would be undermined. Strong evidence of persistence would be indicated by Sharpe ratios in the same order of magnitude as respective excess average returns: descending in value from the top (winning) portfolio to the bottom (losing) portfolio.

A second performance measure is Jensen's Alpha (Jensen: 1968), which determines a security's return adjusted for its exposure to market risk. A positive value for alpha indicates abnormal returns; meaning the investment 'beats' the market (a passive benchmark portfolio representing the security's universe). In the case of mutual fund performance analyzed using the rank portfolio method, a portfolio showing a positive alpha exhibits a persistent outperformance of the market index it's being compared to. Conversely, a negative alpha signals a portfolio which consistently underperforms the market. As with excess returns, strong persistence in mutual fund performance is shown by alpha's decreasing steadily in portfolio rank. Statistically, Jensen's Alpha represented by the intercept in the Capital Asset Pricing Model (CAPM) described in Sharpe (1964) and Lintner (1965):

$$r_{i,t} = \alpha_i + \beta_i RMRF_t + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return of portfolio i in excess of the appropriate risk-free rate in period t, $RMRF_t$ is the excess return of the market index in period t, α_i is the alpha of portfolio i, β_i is the market risk exposure of portfolio i, and $\varepsilon_{i,t}$ is the residual return of portfolio i in month t.

Overall, the rank portfolio based approach is significantly more sophisticated than a contingency table approach. It also provides greater insight into the nature and magnitude of any observed persistence in mutual fund performance. For the purpose of this study, it is convenient to use a rank portfolio approach *à la* Carhart (1997). This will render the results comparable to the majority of previously published mutual fund performance persistence literature. More importantly, specific characteristics of any persistence found can be evaluated in terms of the persistence Huij and Post (2011) find for funds investing in Emerging Markets. The extent to which Latin American funds contribute to the persistence found can thereby be assessed. Nonetheless, a contingency table of initial and subsequent performance rankings can be made in order to determine if there is consistency in fund ranking from period to period. This will eliminate any doubt as to whether winning funds tend to stay in higher ranked portfolios and/or if losing funds do the opposite.

4.0. Data

The mutual fund data are extracted from the Survivor-Bias-Free US Mutual Fund Database compiled by the Centre for Research in Security Prices (CRSP) of the University of Chicago. This database covers monthly return data and wealth of other information including the history of each fund's name, investment style, fee structure, holdings, and asset allocation, for publicly traded open-end mutual funds listed in the United States from January 1962 to present. It is the primary source for mutual fund research and is used by both Carhart (1997) and Huij and Post (2011), among others. A key feature of the database is its classification of funds by investment style. The Lipper classifications (variable: lipper_obj_cd) were implemented at the end of 1999 and are assigned based on how the fund invests. Mutual funds selected for this study are classified by the code LT, describing US funds that "concentrate investments in equity securities with primary trading markets or operations concentrated in the Latin American region or in a single country within this region" (Survivor-Bias-Free US Mutual Fund Guide: 2010). They will be referred to as Latin American funds henceforth. Even though the relatively recent implementation of the Lipper classification system limits the timeframe over which data can be examined to no earlier than January 2000, it would be insensible to examine Latin American funds anytime before that due to the small number in existence before the turn of the millennium. Table 2 provides a summary of some important statistics on the Latin American funds available compared to funds following other region-based investment styles classified by Lipper over the period January 2000 to December 2010.

My sample includes 93 Latin American funds (including both live and dead funds) with the average month including 30 funds with average total net assets of $304 million. Latin American funds exhibit the highest average total return per share per month at 1.23%, followed closely by emerging market funds. This is noticeably higher than the total sample average of 0.34%.

Survival bias is an important issue in mutual fund research. This property is of great important in research on mutual fund performance because the funds that terminate as a result of a merger or liquidation are often among the worst performers. The exclusion of this group of funds from the study would give one an incomplete, and potentially misleading, picture of the performance over the sample period and of the performance likely to prevail in the future. A number of Latin American funds cease operations during the sample period, and would have been omitted from a database which is not survivor-bias-free. The fact that the CRSP US mutual fund database is survivor-bias-free overcomes survivorship bias in the form described in Brown et al. (1992). Carhart (1997) calculates that using Malkiel's (1995) data, which suffers from survivorship bias, and Brown and Goetzmann's (1995) data, which suffers from selection bias, mean mutual fund returns are at least 10 basis points and 20 basis points higher (annually) than those of a data set free of survivorship-bias.

As for the market proxy to be used in the CAPM regressions to calculate market exposure, the S&P Latin America 40 index will be used (hereafter referred to simply as the index). The index tracks equity drawn from the following four major Latin American markets: Brazil, Chile, Mexico, and Peru. It provides broad market exposure through an index that is easy to replicate by investors investing in Latin American stocks that are legally and practically available. The index constituents are leading, large, liquid, blue chip companies from the Latin American markets, capturing 70% of their total market capitalization. Finally, as a proxy for the risk-free rate, the one-month US Treasury-bill (T-bill) rate is used.

Table 2: Time-Series Averages of Cross-Sectional Average Monthly Attributes, Jan. 2000- Dec. 2010

Fund Type	Total Number	Avg Number	Avg MTNA ($ Millions)	Avg MNAV ($ Millions)	Avg MRET (%/month)
All Funds	41975	21270.75	409.03	13.50	0.34%
International Funds	1190	798.70	523.90	14.94	0.22%
Emerging Market Funds	713	264.11	330.64	17.24	1.04%
European Region Funds	305	135.09	209.01	18.45	0.15%
Latin American Funds	93	30.06	303.85	27.34	1.23%

Source: CRSP Survivor-Bias-Free US Mutual Fund Database, 2011

Avg mtna = Total Net Assets as of Month End, Avg mnav = Monthly Net Asset Value Per Share, Avg mret = Total Return Per Share as of Month End

International funds lipper_obj_cd = IF (Funds that invest their assets in securities with primary trading markets outside of the United States)

Emerging market funds lipper_obj_cd = EM (Funds investing in emerging market equity securities, where emerging market is defined by a country's GNP per capita or other economic measures)

European region funds lipper_obj_cd = EU (Funds that concentrate investments in equity securities whose primary trading markets or operations are concentrated in the European region or a single country within this region.)

Latin American funds lipper_obj_cd = LT (Funds that concentrate investments in equity securities with primary trading markets or operations concentrated in the Latin American region or in a single country within this region)

5.0. Performance Persistence

My analysis of persistence in the performance of Latin American funds follows the rank portfolio approach of Hendricks et al. (1993), Carhart (1997), Bollen and Busse (2005) and Huij and Post (2011). The funds in the sample are ranked every month by their excess return (over the one-month T-bill rate) in the past quarter[4] and divided into three equally weighted portfolios (terciles). I decide to form terciles (as in Huij and Post: 2011) instead of deciles, as seen in Cahart (1997), because of the limited number of funds available in the average month (30). Tercile 1 contains the 33.3% best-performing funds, tercile 3 contains the third of funds with the lowest returns, and tercile 2 contains the third of funds in between. Despite the relatively small samples of funds available each month, terciles 1 and 3 are further subdivided into thirds for the sake of added detail and form portfolios 1A, 1B, 1C, 3A, 3B, and 3C; where 1A contains the best ninth performing funds and 3C contains the worst ninth performing funds. Each portfolio's performance is evaluated in the month following its formation. This yields a concatenated time-series of equally-weighted, monthly excess returns for each tercile and ninth of funds[5]. Return distributions for each portfolio can be found in the Appendix 8.1.

5.1. Average Excess & Risk-Adjusted Returns

A summary of descriptive statistics for each portfolio is shown in table 3. The average excess returns of the rank portfolios are strong evidence of persistence in the performance of Latin American mutual funds. Average excess returns decrease almost monotonically in portfolio rank. In other words, the funds that recorded high (low) average monthly excess returns over the past quarter tend to display higher (lower) returns in the following month. Simply put, the data shows that winning funds keep winning, and losing funds keep losing, which is essentially what performance persistence signifies. In fact, the annualized return spread between the top and bottom terciles is as 5.9%. The annualized return spread between the top and bottom ninth of funds is as high as 10.80%. This figure is significantly greater in value than the return spreads noted in research on US funds and emerging market

[4] Average monthly return over the past quarter
[5] The portfolio-formation process is carried out using the MathWorks MATLAB program. Detailed information on the code used, with explanations summarizing each step taken, can be found in Appendix 8.7.

funds. Carhart (1997), for instance, calculates a return spread of 8.04% per annum between the top and bottom decile of US funds, while Hendricks et al. document an annual spread of exactly 5% between top and bottom octiles of US funds. As far as emerging market funds are concerned, Huij and Post (2011) report a return spread of 7.26% per annum between the top and bottom ninth of funds. Comparatively, therefore, Latin American funds exhibit stronger signs of persistence in performance than both US and emerging market funds do. An interesting fact to note is that even the bottom ninth of funds (3C) produces positive excess returns on average. This implies that the worst performing 11% of Latin American funds in any quarter is able to beat the rate of return on the one –month US Treasury Bill (on average). This is not the case for US funds. Carhart (1997) reports a negative average monthly excess return of -0.25%.

Perhaps more important than simple excess returns are Sharpe ratios (table3), which evaluate each portfolio's performance adjusted for risk. If the top portfolios were to contain funds consistently placing risky bets relative to funds in the lower rank portfolios, the Sharpe ratios would not be in the same order of magnitude as the excess returns and undermine, to a certain extent, any persistence in performance shown by the pattern in excess returns. Upon examination, however, the Sharpe ratios decrease steadily down the portfolio ranks and thereby confirm the trend seen in excess returns.

Table 3: Rank Portfolio Descriptive Statistics

Portfolio	Mean Monthly Return	Mean Annualized Return	Median Monthly Return	Standard Deviation	Minimum	Maximum	Sharpe Ratio
1A	2.48%	29.78%	2.25%	9.24%	-24.44%	44.18%	0.27
1B	2.22%	26.65%	2.75%	8.63%	-33.83%	21.99%	0.26
1C	2.01%	24.16%	2.83%	8.35%	-34.63%	21.93%	0.24
1	2.27%	27.26%	2.65%	8.32%	-22.32%	29.31%	0.27
2	1.95%	23.39%	2.90%	8.46%	-34.62%	21.52%	0.23
3	1.78%	21.35%	3.17%	9.34%	-44.65%	22.62%	0.19
3A	1.91%	22.89%	2.71%	8.62%	-35.01%	26.53%	0.22
3B	1.83%	21.91%	2.40%	8.52%	-34.84%	20.64%	0.21
3C	1.58%	18.98%	3.27%	11.42%	-64.10%	27.54%	0.14
1-3 Spread	0.49%	5.90%	-0.52%	-1.02%	22.33%	6.68%	0.08
1A- 3C Spread	0.90%	10.80%	-1.02%	-2.19%	39.66%	16.64%	0.13
Index	1.94%	23.32%	2.77%	8.08%	-31.68%	20.37%	0.24

This table shows the average and median excess returns, volatilities, extremes, and sharpe ratios for terciles and the top and bottom three ninths of Latin American funds ranked monthly by their average monthly return over the past quarter. Each portfolio is evaluated over the single month after its formation.The sample comprises of 98 funds over the January 2000 to December 2010 period.

5.2. Performance Adjusted for Market Exposure

Market-adjusted returns for the rank portfolios are estimated through regression analysis using the single-factor market model mentioned in section 3.2:

$$r_{i,t} = \alpha_i + \beta_i RMRF_t + \varepsilon_{i,t}$$

where $r_{i,t}$ is the return of portfolio i in excess of the appropriate risk-free rate in period t, $RMRF_t$ is the excess return of the market index in period t, α_i is the alpha of portfolio i, β_i is the market risk exposure of portfolio i, and $\varepsilon_{i,t}$ is the residual return of portfolio i in month t. Table 4 shows the alpha's, market risk exposures (RMRF), and adjusted R-squares for each portfolio. More detailed regression outputs are shown in Appendix 8.2.

Interestingly enough, the market betas (RMRF statistics) for the portfolios are very similar to each other. Nevertheless, adjusting the rank portfolio returns for market risk exposure shows a greater spread between top and bottom portfolios compared to that seen between the simple excess returns noted in table 3. Again, there is a strong decreasing pattern in performance from the top to the bottom portfolio. This strongly confirms the existence of persistence in the performance of Latin American funds. The spread in the alphas between the top and bottom ninth of funds is statistically significant at 10.80% per year. It should be noted that the adjusted R-square of the regression of the return spread between portfolios 1A and 3C is very close to 0, implying that the difference in performance between the two rank portfolios is not caused by a significant difference in market exposures.

Nontheless, the top ninth of Latin American funds delivers an extraordinary outperformance of 0.60% monthly; more than 7% per annum, relative to the S&P Latin America 40 Index. This figure is significantly higher than the 2.6% annual outperformance of Carhart's (1997) top-decile of US funds. Hendricks et al. (1993) report an even lower figure for the outperformance of their top octile of funds, at 1.04% per annum. Most surprisingly, however, is a comparison to the outperformance of the top ninth of emerging market funds which is documented at 4.29% per annum, by Huij and Post (2011).

The bottom ninth of Latin American mutual funds underperforms the market by -10.92% per year, a figure substantially more negative than the -2.80 percent underperformance of the bottom ninth of emerging market funds found by Huij and Post (2011). Studies on US funds find figures roughly in between these two values. Hendricks et al. (1993) note an underperformance of -3.25% annually for the bottom octile of funds, while Elton et al. find an underperformance of -4.69% for the bottom decile of funds. Carhart (1997) finds this figure to be -5.40% for the bottom decile of funds. The large underperformance of the bottom ninth of Latin American funds indicates the significant role the losing Latin American funds have in the persistence in performance observed. On the other hand, the outperformance of the top ninth of funds documented is significantly greater than that observed in comparable studies, indicating that the contribution of winning Latin American funds is also relatively larger. Overall, however, the absolute value of portfolio 3C's alpha is greater than the value of portfolio 1A's alpha, leading to the conclusion that the contribution of losing Latin American mutual funds is greater than that of winning Latin American funds in the performance persistence observed.

Table 4: Rank Portfolio CAPM Regression Statistics

Portfolio	Mean Monthly Return	Alpha	Alpha *t*-Statistic	RMRF	RMRF *t*-Statistic	Adj. R-Square
1A	2.48%	0.60%	1.22	0.97	16.19	0.71
1B	2.22%	0.19%	1.07	1.05	49.31	0.96
1C	2.01%	0.03%	0.23	1.02	60.00	0.97
1	2.27%	0.33%	1.65	1.00	41.54	0.94
2	1.95%	-0.07%	-0.62	1.04	78.37	0.98
3	1.78%	-0.41%	-2.06	1.13	46.36	0.95
3A	1.91%	-0.14%	-0.96	1.05	60.57	0.97
3B	1.83%	-0.20%	-1.56	1.04	66.83	0.98
3C	1.58%	-0.91%	-1.89	1.28	22.03	0.82
1-3 Spread	0.49%	0.74%	2.16	-0.13	-3.10	0.08
1A- 3C Spread	0.90%	1.51%	1.68	-0.32	-2.90	0.07

This table shows the average excess returns, Jensen's Alphas with t-statistics, market Betas (RMRF) with t-statistics, and adjusted R-squared values for terciles and top and bottom three ninths of Latin American funds ranked monthly by their average monthly return over the past quarter. Each portfolio is evaluated over the single month after its formation. The sample comprises of 98 funds over the January 2000 to December 2010 period.

The adjusted R-squared figures of the CAPM regressions for the portfolios indicate the proportion of the variance in the portfolio returns explained by the variation in the returns on the S&P Latin America 40 Index over the sample period. The values for the rank portfolios are generally high, meaning the monthly portfolio returns track the movement of the index quite closely. It could therefore be argued that over the sample period analyzed, Latin American mutual fund managers tend not invest actively in order to exploit inefficiencies in the Latin American markets (such as overweighting underpriced stocks and underweighting overpriced stocks relative to the market index), since this would result in far lower adjusted R-squared values. On the other hand, the proven high correlation of equity prices within emerging market economies like those in the Latin American region may also result in the high R-squared statistics for the portfolios. Such high correlations between stocks in a market make deviations from the market index weights less likely to result in significantly lower R-squared values (Morck et al.: 2000).

5.3. Split Sample Analysis

In order to analyze if the persistence in the performance of Latin American funds is evenly spread throughout the entire sample period, or more concentrated in a certain sub period, the sample is split into two periods of identical duration. It is of particular interest to determine whether the persistence prevails in recent years during which the economic environment is far more turbulent than in earlier stages of the sample period. Additionally, the number of funds available in the average month is significantly higher over the second half of the timeframe. Presumably, this can be attributed to the increasing demand in the US market for investment vehicles enabling investment in foreign, and especially emerging, markets. The larger the number of funds in the sample, the stronger the evidence will be for or against the existence of performance persistence in the Latin American mutual fund industry. Average excess returns, Sharpe ratios, alphas, and market exposures for the rank portfolios in each sub-period are shown in table 5. More detailed regression outputs for each sub-period 1 and 2 and found in appendix 8.3 and 8.4, respectively.

Table 5: Split Sample Rank Portfolio Statistics							
Portfolio	**Mean Monthly Return**	**Sharpe Ratio**	**Alpha**	**Alpha *t*-Statistic**	**RMRF**	**RMRF *t*-Statistic**	**Adj. R-Square**
Panel A: Sub-period 1 Jan. 2000- Jun. 2005							
1A	2.31%	0.33	-0.02%	-0.06	0.94	26.37	0.93
1B	2.64%	0.38	0.26%	1.78	0.96	49.35	0.98
1C	2.57%	0.37	0.21%	1.57	0.96	54.50	0.98
1	2.51%	0.36	0.15%	1.03	0.95	49.41	0.98
2	2.55%	0.36	0.11%	0.88	0.99	61.60	0.99
3	2.60%	0.35	0.07%	0.49	1.02	55.31	0.98
3A	2.61%	0.37	0.20%	1.39	0.97	50.81	0.98
3B	2.64%	0.36	0.18%	1.12	1.00	48.41	0.98
3C	2.52%	0.32	-0.16%	-0.68	1.09	34.56	0.96
1-3 Spread	-0.09%	-0.07	0.08%	0.45	-0.07	-2.86	0.13
1A- 3C Spread	-0.21%	-0.07	0.15%	0.34	-0.15	-2.56	0.10
Panel B: Sub-period 2 Jun. 2005- Dec. 2010							
1A	2.74%	0.25	1.19%	1.35	0.99	9.89	0.63
1B	1.94%	0.20	0.22%	0.77	1.10	34.05	0.95
1C	1.61%	0.17	-0.05%	-0.21	1.06	41.60	0.97
1	2.15%	0.23	0.54%	1.58	1.03	26.66	0.93
2	1.51%	0.16	-0.16%	-0.95	1.07	56.69	0.98
3	1.15%	0.11	-0.71%	-2.14	1.19	31.63	0.95
3A	1.39%	0.14	-0.33%	-1.50	1.10	44.48	0.97
3B	1.21%	0.13	-0.46%	-2.45	1.07	50.05	0.98
3C	0.82%	0.06	-1.36%	-1.61	1.40	14.57	0.79
1-3 Spread	1.00%	21.25	1.25%	2.04	-0.16	-2.29	0.07
1A- 3C Spread	1.92%	15.40	2.55%	1.57	-0.41	-2.21	0.07

This table shows the average excess returns, Sharpe ratios, Jensen's Alphas with t-statistics, market Betas (RMRF) with t-statistics, and adjusted R-squared values for terciles and top and bottom three ninths of Latin American funds ranked monthly by their average monthly return over the past quarter. Each portfolio is evaluated over the single month after its formation. Panel A shows the aforementioned statistics calculated for the first half of the sample period (01/2000-06/2005); while panel B does so for the second half of the sample period (06/2005-12/2010).

There appear to be substantial differences between the performance of the rank portfolios in sub-periods 1 and 2. The return spread between the top and bottom ninth of funds is -2.52% per annum in sub-period 1, which is in the opposite order of magnitude as the return spread witnessed over the entire timeframe (table 3). This implies that over the split sample period January 2000 to June 2005, the top ninth performing funds in any quarter performs worse than the bottom ninth performing funds from the same quarter, on average, when evaluating their performance in the month following portfolio formation. This finding is evidence against the existence of any persistence in the performance of Latin American mutual funds. The risk-adjusted returns (Sharpe ratios) for sub-period 1 lead to the same conclusion. The spread in the Sharpe ratios is negative for both the top and bottom terciles and top and bottom ninth of funds, and there is no significant decreasing pattern in returns down the portfolio ranks. The returns adjusted for market exposure (alphas) show some signs of performance persistence, but show a return spread between the top and bottom ninth of funds of just 0.15% per month; a figure significantly lower than that recorded for the entire sample period. All in all, performance persistence in Latin American funds is definitely not evident over the period January 2000 to June 2005.

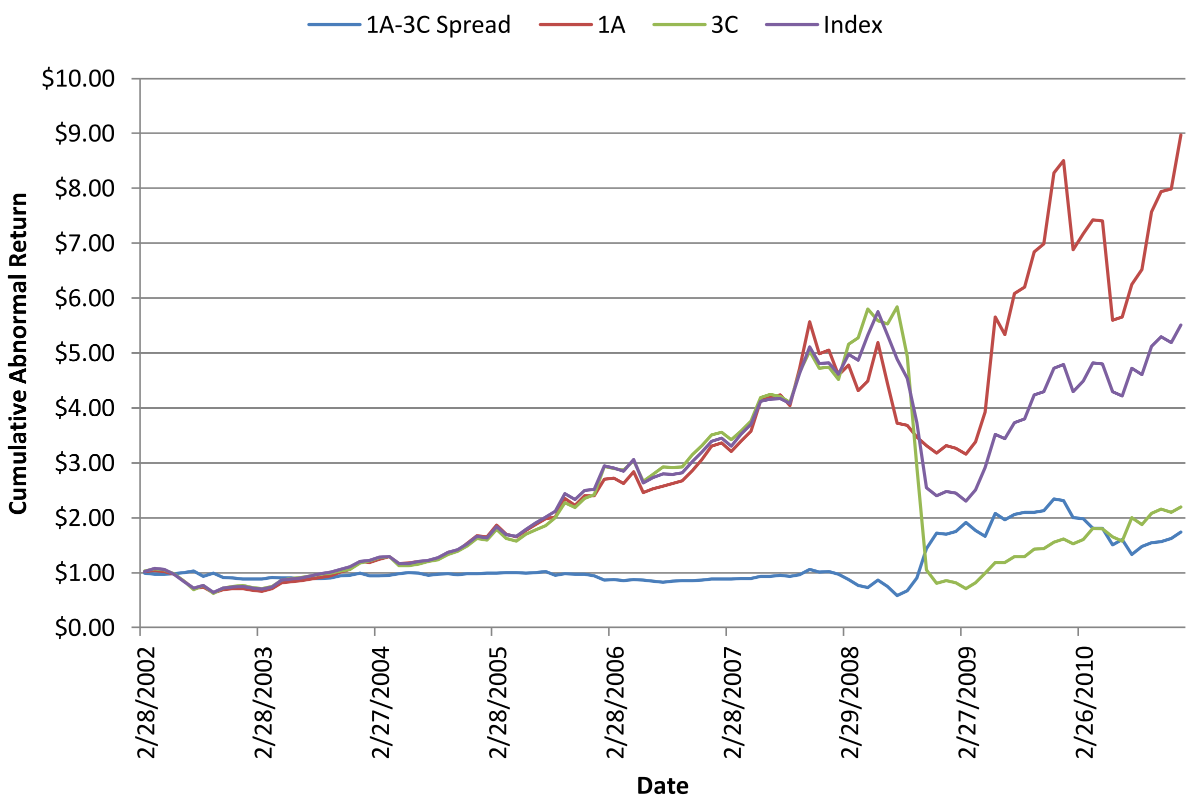
The substantial performance persistence observed over the entire sample period January 2000 to December 2010 in sections 5.1 and 5.2 must therefore be the result of exceedingly strong persistence behavior in sub-period 2. The return spread between the top and bottom ninth of funds is an incredible 23.04% and per annum. The spread in alphas is equally impressive at 30.60% per annum. The top ninth of funds outperforms the market by 14.28% annually while the bottom ninth of funds underperforms by 19.32% annually, on average. These values were 7.20% and 10.92% per annum, respectively, over the entire timeframe. Furthermore, the risk-adjusted returns show a very convincing decreasing pattern down the portfolio ranks.

Ergo, the period 2005 to 2010 shows a very strong persistence in the performance of Latin American mutual funds, while the years 2000 to 2005 fail to show any reasonable sign of persistence at all. This could be due to the second half of the sample period producing a more reliable estimation of average fund performance, seeing that it contains a significantly greater number of funds per month, on average. Conversely, sub-period 1 might fail to produce a valid estimation due to the small number of funds available, which might not be a representative sample. An alternative argument could be made on the idea that well-performing funds set themselves apart from poorly-performing funds more in recent years of financial downturn by maneuvering their way through the volatile markets (especially in Latin America) in a more skilled manor.

5.4. Cumulative Return

In order to gain a better understanding of the level of performance persistence in Latin American mutual funds, it is useful to analyze the spread in the cumulative returns of the portfolios containing the best and worst performing funds. Figure 1 shows the cumulative return spread between the top and bottom ninth of funds, in addition to the cumulative returns of portfolios 1A and 3C on their own and the cumulative return of the S&P Latin America 40 Index for comparison. More detailed cumulative return data can be found in appendix 8.5. The graph confirms the data seen in table 5: the return spread between the bottom and top portfolio is very concentrated in the last part of the full sample period. Portfolios 1A and 3C follow each other closely until 2008, where the return on the bottom ninth of funds plummets. The top ninth of funds seems to be able to limit its losses in this period and is able to generate high positive returns in the subsequent years, while the bottom ninth of funds is not able to do so. This supports the argument made in the previous section: that skilled fund managers showed true expertise where losing funds could not during the recent years of financial crisis.

Figure 1: Rank Portfolio Cumulative Returns

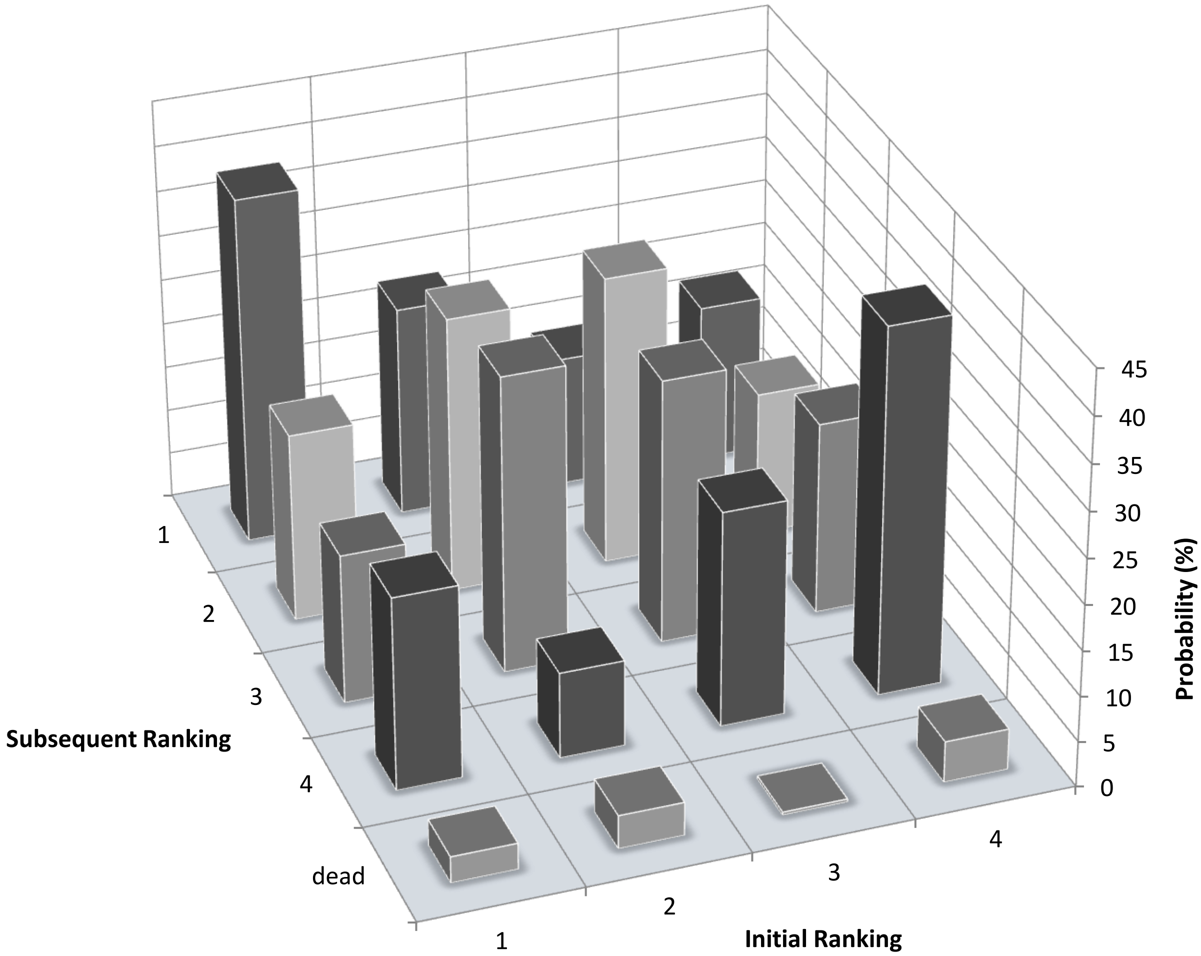


5.5. Consistency in Ranking

An important issue to address is to what extent the fund composition of the rank portfolios stays intact. This ‘consistency in ranking’ of the funds is analyzed by studying the historical probability of a fund currently in portfolio *i* achieving a subsequent ranking of portfolio *j* (or dying). The rankings are from quarter to quarter (no overlap) over the entire January 2000 to December 2010 sample period, with funds sorted into four portfolios (quartiles) based on average excess monthly return for each quarter. Funds that perish during a quarter are placed in a separate category for dead funds. The data is displayed in Figure 2 (p. 23). The raw data can be found in appendix 8.6.

From the figure, it is apparent that winners are significantly more likely to remain winners, and losers are significantly more likely either to remain losers. Losers also show a slightly larger chance of dying over the subsequent period than better performing funds do. Possible explanation for this stability in fund ranking is that funds in the same portfolios might follow similar strategies through time, or that they hold similar securities, also leading to them generating similar returns. Another interesting characteristic is that initial winners (funds in the top quartile) frequently become subsequent losers (funds in the bottom quartile). The opposite is also true. This is strong evidence of gambling behavior by Latin American mutual funds (when the gamble pays off returns are relatively high; while a losing bet results in significantly low returns, making the fund more likely to be in one of the extreme portfolios). Overall, the data in the contingency table enforces an argument in the favour of performance persistence being present amongst Latin American mutual funds over the years 2000 to 2010.

Figure 2: Contingency Table of Inital and Subsequent Quarter Performance Rankings



6.0. Conclusion

This paper documents persistence in the performance of US mutual funds investing in Latin American equity over the period 2000 to 2010. Strong evidence of performance persistence is found, and appears to be concentrated in the second half of the sample period. The spread of average excess returns for the top and bottom ninth of funds ranked by their return over the past quarter is 10.80% per annum; a figure higher than both the 7.26% spread found for emerging market funds and 8.04% spread found for US funds. Furthermore, the top ninth of Latin American funds outperforms the market by 7.20% per annum, while the bottom ninth of funds underperforms the market by -10.92% per annum. These figures are documented at 2.64% and -5.40% for the top and bottom tenth of US funds and 4.29% and -2.80% for the top and bottom ninth of emerging funds. It could therefore be argued that the persistence in the performance of Latin American funds is of a stronger form than that observed in both the American and emerging market mutual fund industries. Additionally, the magnitude of the underperformance of losing funds is greater than the magnitude of the outperformance of winning funds, implying that the losing funds have the greater contribution on the persistence effect.

This paper offers some new insight into the performance of Latin American funds. The relatively large, persisting outperformance of 7.20% per annum produced by winning Latin American funds is consistent with the idea that Latin American markets are less efficient than developed markets and thereby offer active mutual fund managers more opportunities to exploit market anomalies consequently find abnormal returns greater than those able to be generated by US and emerging market mutual funds, on average.

From a more practical standpoint, the large abnormal outperformance of the market by winning funds means that an investor should be able to exploit the ‘hot-hands’ effect mentioned earlier in this paper, by consistently investing in previously well-performing funds.

Further research can be done by constructing Fama-French size (Small-Minus-Big) and value (High-Minus-Low) factors, in addition to a momentum factor (Winner-Minus-Loser), using all stocks in the S&P Latin America 40 Index. Not only would this contribute to research on the size, value and momentum anomalies, but it would also determine to what degree Latin American mutual fund performance can be attributed to differences in SMB, HML, and WML exposures.

An interesting extension would be to elaborate on the regression technique used in this paper by performing multivariate regressions. The simple regressions used in this study do not take into account possible (and probable) correlations among the portfolios of funds that are rebalanced every month based on funds' the previous quarter excess returns. Multivariate tests are more powerful and produce more accurate estimations when there are correlations between the dependent variables (the monthly returns of the rank portfolios, in this context).

7.0. References

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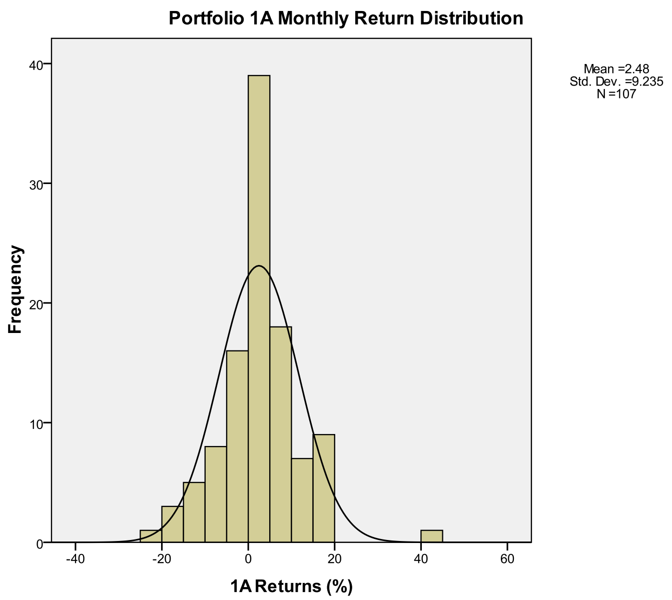
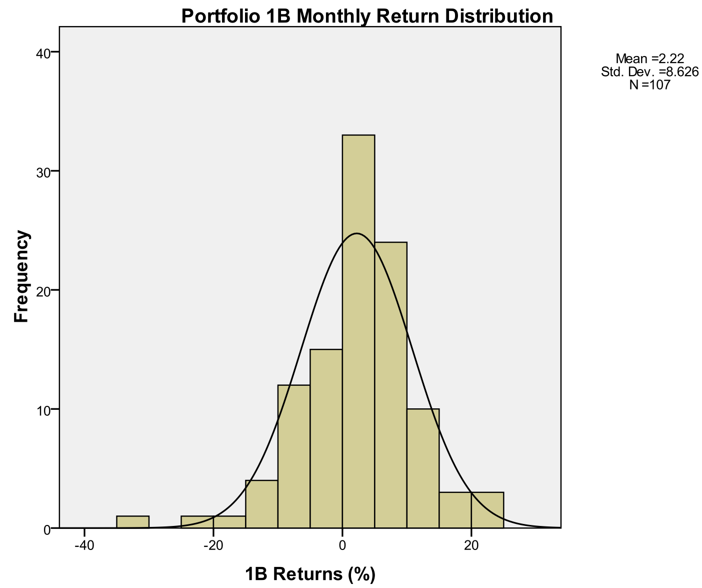
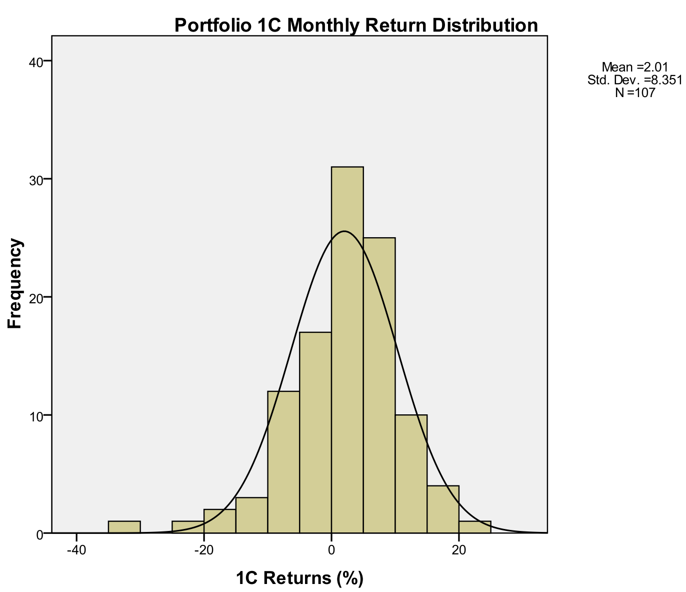
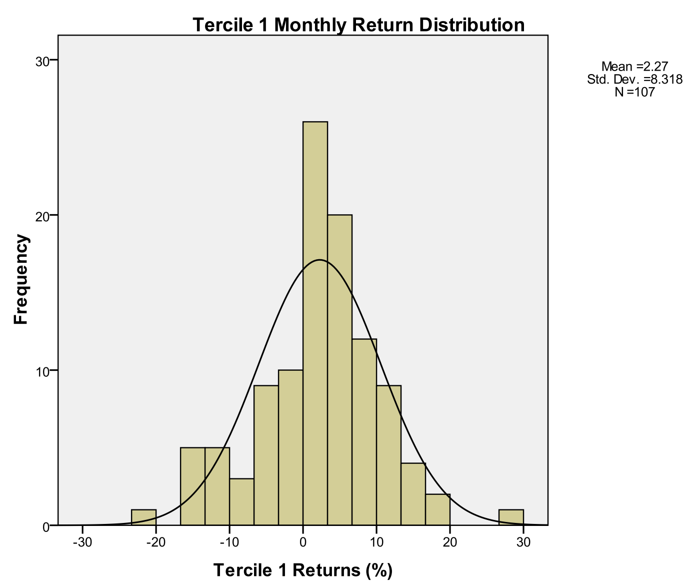
8.0. Appendix

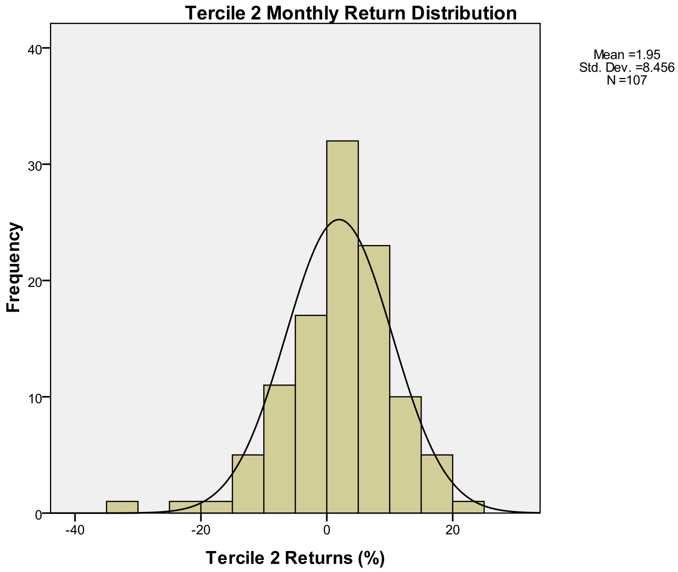
8.1. Histograms showing the distribution of monthly returns of Portfolios 1A, 1B, 1C, 1, 2, 3, 3A, 3B, 3C and that of the S&P Latin America 40 Index.

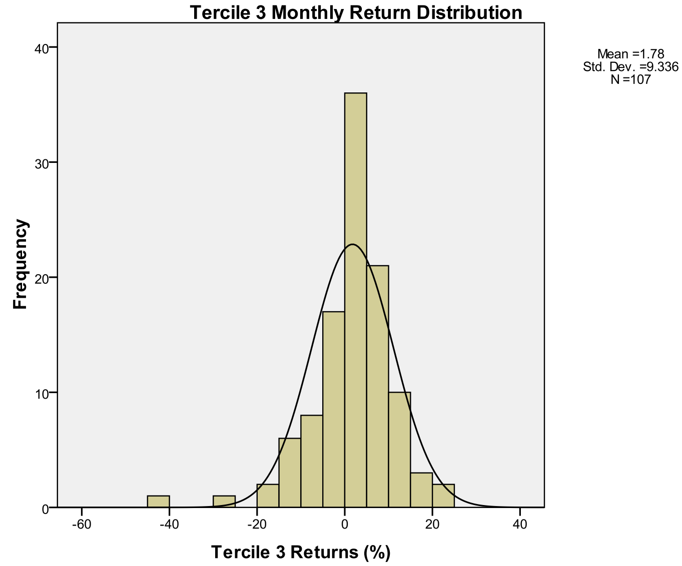


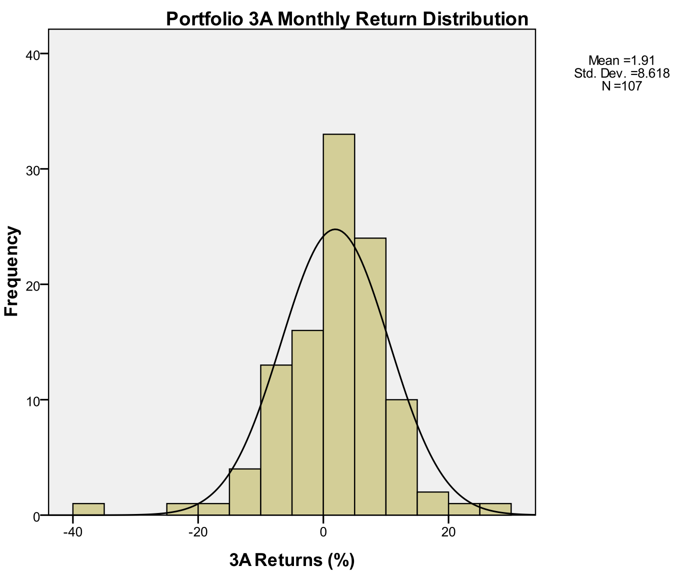


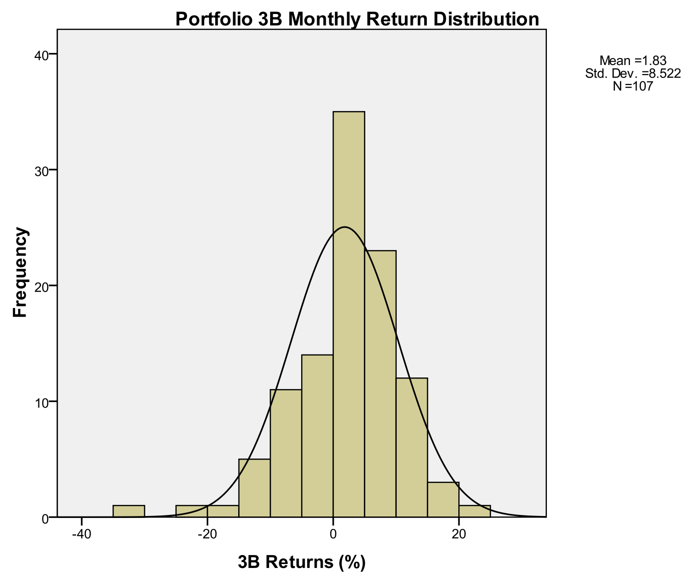


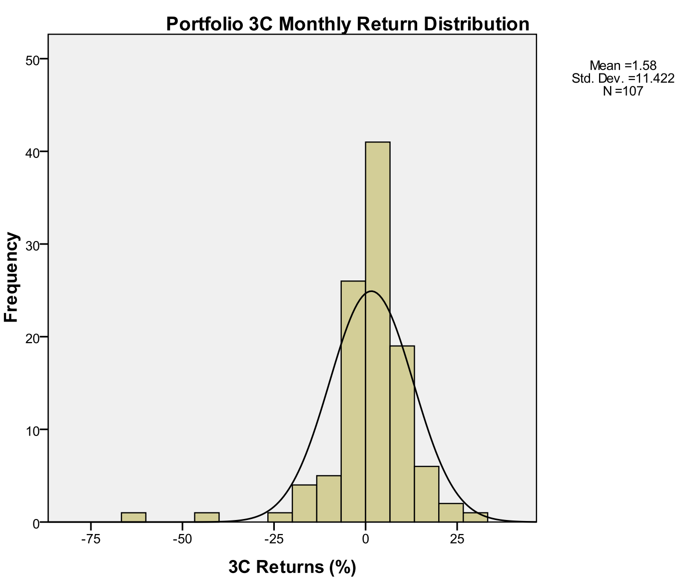


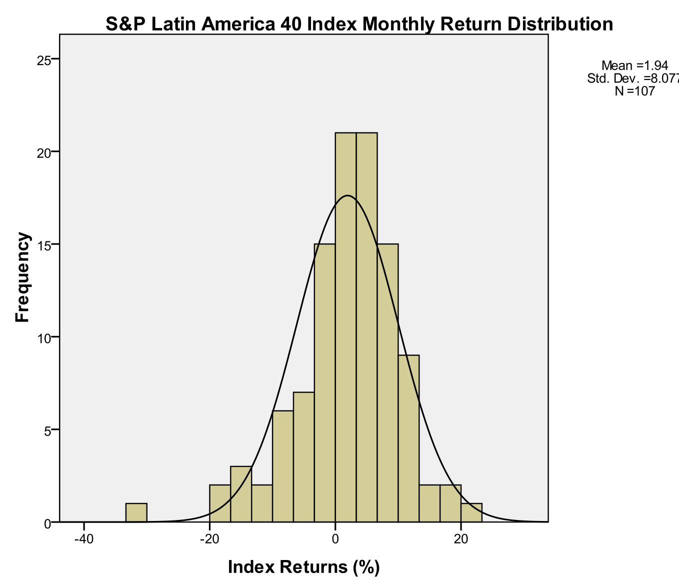

Tercile 2 Monthly Return Distribution
Mean =1.95
Std. Dev. =8.456
N =107
Frequency
Tercile 2 Returns (%)
0
10
20
30
40
-40
-20
0
20


Tercile 3 Monthly Return Distribution
Mean =1.78
Std. Dev. =9.336
N =107
Frequency
Tercile 3 Returns (%)
0
10
20
30
40
-60
-40
-20
0
20
40


Portfolio 3A Monthly Return Distribution
Mean =1.91
Std. Dev. =8.618
N =107
Frequency
3A Returns (%)
0
10
20
30
40
-40
-20
0
20


Portfolio 3B Monthly Return Distribution
Mean =1.83
Std. Dev. =8.522
N =107
Frequency
3B Returns (%)
0
10
20
30
40
-40
-20
0
20


Portfolio 3C Monthly Return Distribution
Mean =1.58
Std. Dev. =11.422
N =107
Frequency
3C Returns (%)
0
10
20
30
40
50
-75
-50
-25
0
25


S&P Latin America 40 Index Monthly Return Distribution
Mean =1.94
Std. Dev. =8.077
N =107
Frequency
Index Returns (%)
0
5
10
15
20
25
-40
-20
0
20

8.2. Regression results for the monthly excess returns of portfolios 1A, 1B, 1C, 1, 2, 3, 3A, 3B, 3C and portfolio 1-3 and 1A-3C spread on the monthly excess returns of the S&P Latin America 40 Index over the entire sample period January 2000 to December 2010.

Portfolio 1A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.845[a]	.714	.711	4.9626612049929E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.604	.494		1.223	.224	-.375	1.582
	RMRF	.966	.060	.845	16.189	.000	.848	1.085

a. Dependent Variable: high1

Portfolio 1B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.979[a]	.959	.958	1.7632762577990E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.188	.175		1.074	.285	-.159	.536
	RMRF	1.046	.021	.979	49.312	.000	1.004	1.088

a. Dependent Variable: high2

Portfolio 1C

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.986[a]	.972	.971	1.4125245778088E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.032	.140		.229	.819	-.246	.311
	RMRF	1.019	.017	.986	60.000	.000	.986	1.053

a. Dependent Variable: high3

Portfolio 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.971[a]	.943	.942	2.0015535528538E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.328	.199		1.646	.103	-.067	.722
	RMRF	1.000	.024	.971	41.544	.000	.952	1.048

a. Dependent Variable: high

Portfolio 2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.992[a]	.983	.983	1.1014352174187E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.068	.110		-.623	.535	-.285	.149
	RMRF	1.038	.013	.992	78.373	.000	1.012	1.064

a. Dependent Variable: middle

Portfolio 3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.976[a]	.953	.953	2.0244831079033E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.414	.201		-2.058	.042	-.814	-.015
	RMRF	1.129	.024	.976	46.358	.000	1.080	1.177

a. Dependent Variable: low

Portfolio 3A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.986[a]	.972	.972	1.4443434089512E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.138	.144		-.958	.340	-.423	.147
	RMRF	1.052	.017	.986	60.574	.000	1.018	1.087

a. Dependent Variable: low1

Portfolio 3B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.988[a]	.977	.977	1.2978389196122E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.201	.129		-1.559	.122	-.457	.055
	RMRF	1.043	.016	.988	66.826	.000	1.012	1.074

a. Dependent Variable: low2

Portfolio 3C

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.907[a]	.822	.820	4.8401322624169E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.910	.481		-1.891	.061	-1.865	.044
	RMRF	1.282	.058	.907	22.029	.000	1.167	1.398

a. Dependent Variable: low3

Portfolio 1- Portfolio 3 Spread

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.289[a]	.084	.075	3.4570797259998E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.742	.344		2.158	.033	.060	1.424
	RMRF	-.129	.042	-.289	-3.095	.003	-.211	-.046

a. Dependent Variable: highlow_spread

<u>Portfolio 1A- Portfolio 3C Spread</u>

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.273[a]	.074	.066	9.0511710388816E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.514	.900		1.682	.096	-.271	3.299
	RMRF	-.316	.109	-.273	-2.904	.004	-.532	-.100

a. Dependent Variable: high1low3_spread

8.3. Regression results for the monthly excess returns of portfolios 1A, 1B, 1C, 1, 2, 3, 3A, 3B, 3C and portfolio 1-3 and 1A-3C spread on the monthly excess returns of the S&P Latin America 40 Index over sub-period 1: January 2000 to June 2005.

Portfolio 1A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.967[a]	.934	.933	1.8229305323961E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.016	.270		-.058	.954	-.559	.527
	RMRF	.941	.036	.967	26.369	.000	.869	1.013

a. Dependent Variable: high1

Portfolio 1B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.990[a]	.980	.980	.9955592626357

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.263	.148		1.784	.081	-.033	.560
	RMRF	.962	.019	.990	49.350	.000	.922	1.001

a. Dependent Variable: high2

Portfolio 1C

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.992[a]	.984	.983	.8955320217269

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.208	.133		1.570	.123	-.058	.475
	RMRF	.955	.018	.992	54.499	.000	.920	.990

a. Dependent Variable: high3

Portfolio 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.990[a]	.980	.980	.9858624731409

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.151	.146		1.032	.307	-.143	.444
	RMRF	.953	.019	.990	49.410	.000	.915	.992

a. Dependent Variable: high

Portfolio 2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.994[a]	.987	.987	.8201174304648

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.107	.122		.878	.384	-.138	.351
	RMRF	.989	.016	.994	61.596	.000	.956	1.021

a. Dependent Variable: middle

Portfolio 3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.992[a]	.984	.984	.9441578067806

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.069	.140		.494	.623	-.212	.350
	RMRF	1.022	.018	.992	55.314	.000	.985	1.059

a. Dependent Variable: low

Portfolio 3A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.991[a]	.981	.981	.9784650593608

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.201	.145		1.389	.171	-.090	.493
	RMRF	.973	.019	.991	50.806	.000	.935	1.011

a. Dependent Variable: low1

Portfolio 3B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.990[a]	.980	.979	1.0509406762789E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.175	.156		1.121	.268	-.138	.487
	RMRF	.996	.021	.990	48.413	.000	.955	1.037

a. Dependent Variable: low2

Portfolio 3C

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.980[a]	.961	.960	1.6049038277987E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.161	.238		-.678	.501	-.639	.317
	RMRF	1.086	.031	.980	34.563	.000	1.023	1.149

a. Dependent Variable: low3

Portfolio 1- Portfolio 3 Spread

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.379[a]	.143	.126	1.2273604734085E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.082	.182		.449	.655	-.284	.447
	RMRF	-.069	.024	-.379	-2.863	.006	-.117	-.020

a. Dependent Variable: high-low

Portfolio 1A- Portfolio 3C Spread

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.344[a]	.118	.100	2.8870336956453E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.146	.428		.340	.735	-.714	1.005
	RMRF	-.145	.057	-.344	-2.564	.013	-.258	-.031

a. Dependent Variable: high1-low3

8.4. Regression results for the monthly excess returns of portfolios 1A, 1B, 1C, 1, 2, 3, 3A, 3B, 3C and portfolio 1-3 and 1A-3C spread on the monthly excess returns of the S&P Latin America 40 Index over sub-period 2: June 2005 to December 2010.

Portfolio 1A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.800[a]	.640	.634	6.5694460812411E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.190	.884		1.346	.184	-.582	2.962
	RMRF	.990	.100	.800	9.892	.000	.789	1.190

a. Dependent Variable: high1

Portfolio 1B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.977[a]	.955	.954	2.1164189726516E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.220	.285		.773	.443	-.350	.791
	RMRF	1.098	.032	.977	34.045	.000	1.033	1.162

a. Dependent Variable: high2

Portfolio 1C

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.984[a]	.969	.969	1.6689423550499E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.047	.225		-.207	.836	-.497	.404
	RMRF	1.058	.025	.984	41.599	.000	1.007	1.108

a. Dependent Variable: high3

Portfolio 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.963[a]	.928	.927	2.5399382859321E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	.541	.342		1.584	.119	-.144	1.226
	RMRF	1.031	.039	.963	26.660	.000	.954	1.109

a. Dependent Variable: high

Portfolio 2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.992[a]	.983	.983	1.2363861508394E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.159	.166		-.954	.344	-.492	.175
	RMRF	1.068	.019	.992	56.691	.000	1.030	1.105

a. Dependent Variable: middle

Portfolio 3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.974[a]	.948	.947	2.4712621514755E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.711	.333		-2.139	.037	-1.378	-.045
	RMRF	1.190	.038	.974	31.625	.000	1.115	1.266

a. Dependent Variable: low

Portfolio 3A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.986[a]	.973	.972	1.6228096545792E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.327	.218		-1.499	.140	-.765	.110
	RMRF	1.099	.025	.986	44.478	.000	1.050	1.149

a. Dependent Variable: low1

Portfolio 3B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.989[a]	.979	.978	1.4031175612740E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-.462	.189		-2.445	.018	-.840	-.083
	RMRF	1.070	.021	.989	50.052	.000	1.027	1.113

a. Dependent Variable: low2

Portfolio 3C

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.891[a]	.794	.790	6.2890576146853E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-1.363	.846		-1.611	.113	-3.060	.333
	RMRF	1.395	.096	.891	14.565	.000	1.203	1.587

a. Dependent Variable: low3

Portfolio 1- Portfolio 3 Spread

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.295[a]	.087	.071	4.5571380477016E0

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	1.253	.613		2.043	.046	.024	2.482
	RMRF	-.159	.069	-.295	-2.291	.026	-.298	-.020

a. Dependent Variable: high-low

Portfolio 1A- Portfolio 3C Spread

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.285[a]	.081	.065	1.2060810761477E1

a. Predictors: (Constant), RMRF

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.553	1.623		1.573	.121	-.699	5.806
	RMRF	-.405	.184	-.285	-2.207	.032	-.774	-.037

a. Dependent Variable: high1-low3

8.5. Cumulative returns for portfolios 1A and 3C, the spread between the returns of portfolios 1A and C, and the S&P Latin America 40 Index.

Table 8.5: Rank Portfolio Cumulative Returns	
Portfolio	**Cumulative Return**
1A	896.97%
3C	219.61%
1A- 3C Spread	173.88%
Index	550.69%

8.6. Consistency in Ranking Data

Table 8.6: Consistency in Ranking					
		Initial Ranking *i*			
		4	**3**	**2**	**1**
Subsequent Ranking *j*	**1**	17.61111	14.53061	23.42404	38.6644
	2	16.04649	32.16327	30.66553	20.8458
	3	21.31519	29.26984	32.81066	16.46372
	4	40.52834	23.71882	9.462585	21.16893
	dead	4.498866	0.31746	3.637188	2.857143

Table 8.7 shows the conditional probability (in percent) for a fund of achieving a subsequent portfolio ranking of quartile j (or dying), given an initial ranking of quartile i

8.1. MATLAB commands used in the portfolio-formation process and subsequently in the generation of portfolio returns.

a. Subtracting the risk-free rate from the raw returns to calculate time-series of excess returns for each individual mutual fund:

```
function [Highaverage,Middleaverage,Lowaverage] = excess(data,z)


   A=mean(data(:,z:z+2),2);
   B=data(:,z+3);

   p=0;
  [sorted,whichfund]=sort(A);
   for i=1:93
       if B(whichfund(i))>=0 || B(whichfund(i))<=0
           p=p+1;
           Sortededit(p)=sorted(i);
           whichfundedit(p)=whichfund(i);
       end
   end


   t=0;

   for i=1:p
      if Sortededit(i)>=0 || Sortededit(i)<=0
          t=t+1;
      else
      end
   end
   t;
   Sortededit=Sortededit(1:t);
   whichfundedit=whichfundedit(1:t);
   groupsize=round(t/3);

   High=Sortededit(2*groupsize+1:t);
   Highwhich=whichfundedit(2*groupsize+1:t)';

   Middle=Sortededit(groupsize+1:2*groupsize);
   Middlewhich=whichfundedit(groupsize+1:2*groupsize)';

   Low=Sortededit(1:groupsize);
   Lowwhich=whichfundedit(1:groupsize)';

   Highaverage=mean(B(Highwhich));
   Middleaverage=mean(B(Middlewhich));
   Lowaverage=mean(B(Lowwhich));
end
```

b. Splitting the time-series of mutual fund returns into rank portfolios based on past quarter performance:

```
function
[Highaverage1,Highaverage2,Highaverage3,Highaverage,Middleaverage,Lowavera
ge,Lowaverage1,Lowaverage2,Lowaverage3] = qav(data,z)
   A=mean(data(:,z:z+2),2); %takes average of quarter
   B=data(:,z+3); %takes data of the following month
   p=0;
  [sorted,whichfund]=sort(A); %sorts data
   for i=1:93  % this controls if there is data in the following month,
and removes it from list
       if B(whichfund(i))>=0 || B(whichfund(i))<=0
           p=p+1;
           Sortededit(p)=sorted(i);
           whichfundedit(p)=whichfund(i);
       end
   end



   t=0;

   for i=1:p %this counts how many data is in the clean sorted list
      if Sortededit(i)>=0 || Sortededit(i)<=0
          t=t+1;
      else
      end
   end
   t;
   %the following splits the data into 3 groups
   Sortededit=Sortededit(1:t);

   whichfundedit=whichfundedit(1:t);
   check=B(whichfundedit); %this is control variable
   sizecheck=size(check) %control
   groupsize=round(t/3); %calc groups sizes

   High=Sortededit(2*groupsize+1:t); %high group
   Highwhich=whichfundedit(2*groupsize+1:t)'; %high group which fund

   Middle=Sortededit(groupsize+1:2*groupsize); %middle group
   Middlewhich=whichfundedit(groupsize+1:2*groupsize)'; %middle group
which fund

   Low=Sortededit(1:groupsize); %low group which fund
   Lowwhich=whichfundedit(1:groupsize)'; %low group which fund


   %splitting highest into 3 parts
   sizeHigh=size(High,2);
   groupsizeHigh=round(sizeHigh/3);

   High1=High(2*groupsizeHigh+1:sizeHigh);
```

```
    Highwhich1=Highwhich(2*groupsizeHigh+1:sizeHigh)';

    High2=High(groupsizeHigh+1:2*groupsizeHigh);
    Highwhich2=Highwhich(groupsizeHigh+1:2*groupsizeHigh)';

    High3=High(1:groupsizeHigh);
    Highwhich3=Highwhich(1:groupsizeHigh)';


    %splitting lowest into 3 parts
    sizeLow=size(Low,2);
    groupsizeLow=round(sizeLow/3);

    Low1=Low(2*groupsizeLow+1:sizeLow);
    Lowwhich1=Lowwhich(2*groupsizeLow+1:sizeLow)';

    Low2=Low(groupsizeLow+1:2*groupsizeLow);
    Lowwhich2=Lowwhich(groupsizeLow+1:2*groupsizeLow)';

    Low3=Low(1:groupsizeLow);
    Lowwhich3=Lowwhich(1:groupsizeLow)';



    %averages
    Highaverage1=mean(B(Highwhich1));
    Highaverage2=mean(B(Highwhich2));
    Highaverage3=mean(B(Highwhich3));

    Highaverage=mean(B(Highwhich));
    Middleaverage=mean(B(Middlewhich));
    Lowaverage=mean(B(Lowwhich));

    Lowaverage1=mean(B(Lowwhich1));
    Lowaverage2=mean(B(Lowwhich2));
    Lowaverage3=mean(B(Lowwhich3));
end
```

c. Calculating the following month returns for rank portfolios and then repeating for the entire sample period:

```
function
[FinalHighAv1,FinalHighAv2,FinalHighAv3,FinalHighAv,FinalMiddleAv,FinalLow
Av,FinalLowAv1,FinalLowAv2,FinalLowAv3,Highaverage1,Highaverage2,Highavera
ge3,Highaverage,Middleaverage,Lowaverage,Lowaverage1,Lowaverage2,Lowaverag
e3]= repeat
data=xlsread('Book1.xlsx');
%this function reads the data and calculated the final avrages

for l=1:107 %this calculates the data for the groups after comparing the
quater to the following month. It does this for all 107 periods and stores
it in matrices

[Highaverage1(l),Highaverage2(l),Highaverage3(l),Highaverage(l),Middleaver
age(l),Lowaverage(l),Lowaverage1(l),Lowaverage2(l),Lowaverage3(l)] =
qav(data,l);
end
    %following lines calculates the final averages for each groups
    FinalHighAv1=mean(Highaverage1);
    FinalHighAv2=mean(Highaverage2);
    FinalHighAv3=mean(Highaverage3);

    FinalHighAv=mean(Highaverage);
    FinalMiddleAv=mean(Middleaverage);
    FinalLowAv=mean(Lowaverage);

    FinalLowAv1=mean(Lowaverage1);
    FinalLowAv2=mean(Lowaverage2);
    FinalLowAv3=mean(Lowaverage3);
end


function
[FinalHighAv1,FinalHighAv2,FinalHighAv3,FinalHighAv,FinalMiddleAv,FinalLow
Av,FinalLowAv1,FinalLowAv2,FinalLowAv3] = repeatexcess
data=xlsread('Book1.xlsx');
rf=xlsread('rf.xls');
rftable=repmat(rf',93,1);

editdata=data-rftable;

for l=1:107

[Highaverage1(l),Highaverage2(l),Highaverage3(l),Highaverage(l),Middleaver
age(l),Lowaverage(l),Lowaverage1(l),Lowaverage2(l),Lowaverage3(l)] =
qav(editdata,l);
end
    FinalHighAv1=mean(Highaverage1);
    FinalHighAv2=mean(Highaverage2);
    FinalHighAv3=mean(Highaverage3);
```

```
    FinalHighAv=mean(Highaverage);
    FinalMiddleAv=mean(Middleaverage);
    FinalLowAv=mean(Lowaverage);

    FinalLowAv1=mean(Lowaverage1);
    FinalLowAv2=mean(Lowaverage2);
    FinalLowAv3=mean(Lowaverage3);
end
```

d. Calculating rank portfolio returns for the two sub-periods instead of the entire sample period:

```
function
[FinalHighAv1,FinalHighAv2,FinalHighAv3,FinalHighAv,FinalMiddleAv,FinalLow
Av,FinalLowAv1,FinalLowAv2,FinalLowAv3]= repeatexcess1to54
% periods 1-54
data=xlsread('Book1.xlsx');
rf=xlsread('rf.xls');
rftable=repmat(rf',93,1);

editdata=data-rftable;

for l=1:54

[Highaverage1(l),Highaverage2(l),Highaverage3(l),Highaverage(l),Middleaver
age(l),Lowaverage(l),Lowaverage1(l),Lowaverage2(l),Lowaverage3(l)] =
qav(editdata,l);
end
    FinalHighAv1=mean(Highaverage1);
    FinalHighAv2=mean(Highaverage2);
    FinalHighAv3=mean(Highaverage3);

    FinalHighAv=mean(Highaverage);
    FinalMiddleAv=mean(Middleaverage);
    FinalLowAv=mean(Lowaverage);

    FinalLowAv1=mean(Lowaverage1);
    FinalLowAv2=mean(Lowaverage2);
    FinalLowAv3=mean(Lowaverage3);
end


function
[FinalHighAv1,FinalHighAv2,FinalHighAv3,FinalHighAv,FinalMiddleAv,FinalLow
Av,FinalLowAv1,FinalLowAv2,FinalLowAv3] = repeatexcess54to107
% periods 54-107
data=xlsread('Book1.xlsx');
rf=xlsread('rf.xls');
rftable=repmat(rf',93,1);

editdata=data-rftable;
```

```
for l=54:107

[Highaverage1(l),Highaverage2(l),Highaverage3(l),Highaverage(l),Middleaver
age(l),Lowaverage(l),Lowaverage1(l),Lowaverage2(l),Lowaverage3(l)] =
qav(editdata,l);
end
    FinalHighAv1=mean(Highaverage1);
    FinalHighAv2=mean(Highaverage2);
    FinalHighAv3=mean(Highaverage3);

    FinalHighAv=mean(Highaverage);
    FinalMiddleAv=mean(Middleaverage);
    FinalLowAv=mean(Lowaverage);

    FinalLowAv1=mean(Lowaverage1);
    FinalLowAv2=mean(Lowaverage2);
    FinalLowAv3=mean(Lowaverage3);
end
```

e. Calculating the probability of a fund being in one (of four) rank portfolios and then being in another (or dead):

```
function [P]=graph(data,q)

%data=xlsread('Book1.xlsx');
sortedA=[];
sortedAedit=[];
whichfundA=[];
whichfundAedit=[];
sortedB=[];
sortedBedit=[];
whichfundB=[];
whichfundBedit=[];

period1=mean(data(:,q:q+2),2);
period2=mean(data(:,q+3:q+5),2);

[sortedA,whichfundA]=sort(period1);
[sortedB,whichfundB]=sort(period2);


ta=0;
for i=1:93
    if sortedA(i)>=0 || sortedA(i)<=0
        ta=ta+1;
        sortedAedit(ta)=sortedA(i);
        whichfundAedit(ta)=whichfundA(i);
    else
    end
end

tb=0;
```

```
for i=1:93
    if sortedB(i)>=0 || sortedB(i)<=0
        tb=tb+1;
        sortedBedit(tb)=sortedB(i);
        whichfundBedit(tb)=whichfundB(i);
    else
    end
end
%sortinggroups
groupsizeA=round(ta/4);
groupsizeB=round(tb/4);

A1=whichfundAedit(1:groupsizeA);
A2=whichfundAedit(groupsizeA+1:2*groupsizeA);
A3=whichfundAedit(2*groupsizeA+1:3*groupsizeA);
A4=whichfundAedit(3*groupsizeA+1:ta);

B1=whichfundBedit(1:groupsizeB);
B2=whichfundBedit(groupsizeB+1:2*groupsizeB);
B3=whichfundBedit(2*groupsizeB+1:3*groupsizeB);
B4=whichfundBedit(3*groupsizeB+1:tb);

%Percentage Calculator
P=zeros(5,4);

P(1,1)=(size(intersect(A1,B1),2)/groupsizeA)*100;
P(2,1)=(size(intersect(A1,B2),2)/groupsizeA)*100;
P(3,1)=(size(intersect(A1,B3),2)/groupsizeA)*100;
P(4,1)=(size(intersect(A1,B4),2)/groupsizeA)*100;

P(1,2)=(size(intersect(A2,B1),2)/groupsizeA)*100;
P(2,2)=(size(intersect(A2,B2),2)/groupsizeA)*100;
P(3,2)=(size(intersect(A2,B3),2)/groupsizeA)*100;
P(4,2)=(size(intersect(A2,B4),2)/groupsizeA)*100;

P(1,3)=(size(intersect(A3,B1),2)/groupsizeA)*100;
P(2,3)=(size(intersect(A3,B2),2)/groupsizeA)*100;
P(3,3)=(size(intersect(A3,B3),2)/groupsizeA)*100;
P(4,3)=(size(intersect(A3,B4),2)/groupsizeA)*100;

P(1,4)=(size(intersect(A4,B1),2)/(ta-(3*groupsizeA)))*100;
P(2,4)=(size(intersect(A4,B2),2)/(ta-(3*groupsizeA)))*100;
P(3,4)=(size(intersect(A4,B3),2)/(ta-(3*groupsizeA)))*100;
P(4,4)=(size(intersect(A4,B4),2)/(ta-(3*groupsizeA)))*100;

P(5,1)=100-sum(P(:,1));
P(5,2)=100-sum(P(:,2));
P(5,3)=100-sum(P(:,3));
P(5,4)=100-sum(P(:,4));


end
```

f. Repeating the probability calculations from (e.) for the entire sample period to produce the contingency table data:

```
function [Pfinal] = repeatgraph
data=xlsread('Book1.xlsx');
q=[1:3:108]
[P1]=graph(data,q(1))
[P2]=graph(data,q(2))
[P3]=graph(data,q(3))
[P4]=graph(data,q(4))
[P5]=graph(data,q(5))
[P6]=graph(data,q(6))
[P7]=graph(data,q(7))
[P8]=graph(data,q(8))
[P9]=graph(data,q(9))
[P10]=graph(data,q(10))
[P11]=graph(data,q(11))
[P12]=graph(data,q(12))
[P13]=graph(data,q(13))
[P14]=graph(data,q(14))
[P15]=graph(data,q(15))
[P16]=graph(data,q(16))
[P17]=graph(data,q(17))
[P18]=graph(data,q(18))
[P19]=graph(data,q(19))
[P20]=graph(data,q(20))
[P21]=graph(data,q(21))
[P22]=graph(data,q(22))
[P23]=graph(data,q(23))
[P24]=graph(data,q(24))
[P25]=graph(data,q(25))
[P26]=graph(data,q(26))
[P27]=graph(data,q(27))
[P28]=graph(data,q(28))
[P29]=graph(data,q(29))
[P30]=graph(data,q(30))
[P31]=graph(data,q(31))
[P32]=graph(data,q(32))
[P33]=graph(data,q(33))
[P34]=graph(data,q(34))
[P35]=graph(data,q(35))

Pfinal=[P1+P2+P3+P4+P5+P6+P7+P8+P9+P10+P11+P12+P13+P14+P15+P16+P17+P18+P19
+P20+P21+P22+P23+P24+P25+P26+P27+P28+P29+P30+P31+P32+P33+P34+P35]/35

end
```