ERASMUS UNIVERSITY ROTTERDAM
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(Residual) Momentum and Volatility Strategies in Emerging Markets

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Abstract

In this research, I document the efficiency of the residual momentum strategy and its outperformance relative to its peer conventional momentum strategy in the emerging markets equity market. Using an innovative way to gather equity data from Thomson Datastream, I show that the residual momentum strategy yields significant positive returns with a higher Sharpe ratio than the conventional momentum strategy in a market constituted by the ten largest emerging markets. Moreover, I find substantial evidence that volatility strategies fail to generate positive abnormal returns for investors.

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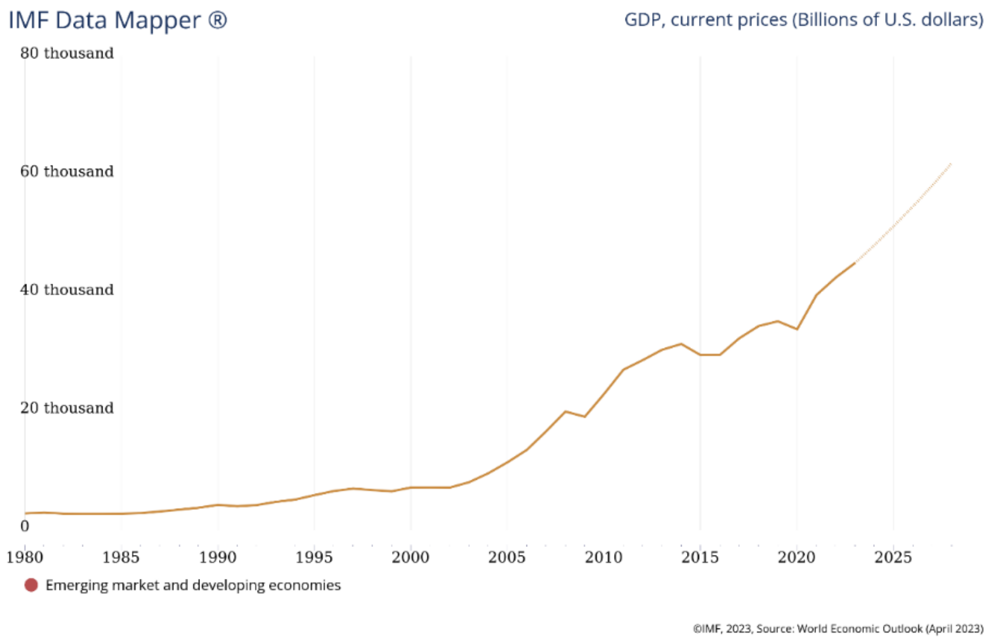
1. Introduction

In the last decades, capital restrictions have loosened, and investors have gained the option to invest in new markets, making emerging markets even more relevant for asset pricing research. According to the Institute of International Finance (IFF), investment flows in emerging markets have significantly increased over the last years, driven by improving economic prospects in those markets. As seen in Figure 1.1, developing countries' GDP figures have been dramatically increasing over the last 22 years. One would expect that such growth makes investing in emerging markets more appealing due to the opportunities arising and the markets' momentum. It is thus crucial for investors with emerging markets investing appetite to be further informed about the forces that drive returns in those markets and use that knowledge in order to successfully extract returns from them. However, research on emerging markets has been relatively limited compared to developed markets research, due to the challenges of accessing appropriate and accurate data. I thus try to identify the sources of returns in emerging markets assets, using a data gathering method that allows me to maximize my scope of research in those markets.

Figure 1.1 Emerging and Developing Countries GDP, 1980-2028



One of my main findings is that risk in the emerging markets is not compensated in the form of returns. Moreover, the residual momentums strategy outperforms the momentum strategy of Jegadeesh and Titman (1993), while having a lower exposure to the risk factors, making the strategy extremely efficient in the long-run in these markets, and volatility of stocks-based strategies fails to generate positive returns.

In the most conventional asset pricing theories, asset prices are closely tied to the assets' risk. The foundation of the dominant theories has been assuming market efficiency, and thus researchers have repeatedly tried to explain the expected returns of the stocks by arguing that the returns are in fact a required compensation by the investors holding stocks that are exposed to risk factors. In other words, investors holding risky stocks expect to be compensated for their choices, and the efficient market should accommodate that.

The Capital Asset Pricing Model (CAPM) introduced by Sharpe (1964) and Linter (1965) was one of the first approaches to investigate the relationship between the expected returns and the systematic, or market, risk. Market risk is any kind of risk that is market movements dependent and cannot be diversified away by holding a portfolio of different stocks. Most common examples of market risk are global macro events that drive asset prices up or down. According to the CAPM, the expected returns of stocks are higher (lower) for stocks that have higher (lower) exposure to market risk, which is interpreted as the compensation required by investors for the risk that they bear by investing in the stock. The market betas (β), capturing stock sensitivity to market moves, and thus the sensitivity of stocks and portfolios to market risk, have ever since been the cornerstone of asset pricing and broadly used as the main risk factor capturing the sensitivity of portfolios to systematic risk.

Fama & French (1993) extended the research on the average cross-section returns of U.S. stocks, finding evidence that CAPM by itself was not sufficient to explain the cross-sectional returns. They documented evidence that the model combined with two further control variables, the '*size'* and the '*value'* of firms, accounting for the market capitalization and the book-to-market of the stocks respectively, actually has significant explanatory power in explaining the cross-sectional returns of US stocks. They presented evidence that stocks of smaller market capitalization and higher book-to-market ratios have higher expected cross-sectional average returns. As one of their basic assumptions lies within the efficient market hypothesis (EMH) (Fama E., 1970), they argued that since smaller (bigger) firms and high (low) book-to-market ratio firms have higher (lower) returns, smaller and cheaper firms must actually have some additional risk embedded in them. Hence, investors that invest in those stocks require extra compensation for the risk that they bear, raising the assets' expected returns. Possible economic explanations provided by academics are that illiquid stocks, which usually are small size stocks, are riskier as investors might have to pay a higher bid-ask spread in all transactions. As Fama & French (1993) believe in market efficiency, they argue that investors are only compensated for bearing systematic risk that cannot be diversified away. Idiosyncratic risk is not priced by the markets and investors holding idiosyncratic risk-exposed stocks are not compensated for it.

The 'β', '*value',* and '*size'* factors, commonly known as the 'usual suspects' have been ever since used as commonly used risk factors by most researchers. In many cases, the usual suspects have significant power in explaining the cross-section of stock returns, however, not always sufficient in explaining them. Thus, many academics have researched further, and have documented evidence that many more factors add additional explanatory power about expected returns, to the conventional risk models. The most interesting finding is that these factors are not always associated with risk, and the belief that return is always a compensation for risk is severely challenged. The EMH argues that it should be impossible for investors to exploit market inefficiencies and beat the market as all available information is already priced in assets (Fama E., 1970). Factors that have had evidently significant explanatory power for the cross-sectional returns of stocks but have been contradicting the EMH and at the same time might be explained by economic theory, have been commonly known in the world of finance as anomalies. The anomalies definition however remains ambiguous in the finance literature. Anomalies have not been associated with a risk side of stocks, as researchers have not been able to associate them with any known risk factors. It remains up to day hard to explain the returns of stocks exposed to specific anomalies, and we are not certain if portfolio-building strategies that base their stock picking on anomalies actually yield abnormal returns or just a coated compensation for the extra risk that the picked stocks bear. Identifying existing anomalies adds great value for relevant market investors. Risk seeking investors might exhibit appetite for assuming extra risk and thus potential compensation for it, but risk averse investors would most likely prefer to assume less risk, but keep their profits positive and stable. That can be achieved by using the anomalies-based strategies, that mitigate market risks to a certain degree, but allow for positive returns in the long-run.

Momentum is one of the most well-known and researched anomalies over the years, and the first one I find to be alive and well in the emerging markets. According to the momentum effect, stocks that have performed well in the past will keep performing well in the future, and stocks that have performed poorly in the past will continue performing poorly in the future. The momentum strategy that buys winner portfolios while sorting loser portfolios, in order to extract wealth by exploiting the momentum anomaly, has been proven to be efficient, persistent, and robust across different markets through the years. What makes the momentum effect particularly interesting is the fact that there is no concrete rationale behind what makes past winners continue outperforming, while past losers keep continuing underperforming. One can easily tell that the momentum effect challenges the efficient market hypothesis. It is rather puzzling, why the past performance of stocks would be a good predictor of their future performance. If all available information on stocks has already been priced in asset prices, then it becomes unclear why past winners shall keep outperforming, while past losers shall keep underperforming. The majority of plausible explanations seek interpretation in behavioral and psychological factors. Investor sentiment has played a significant role in shaping the market dynamics, making asset prices deviate from their fundamental values and driving the momentum returns up. Among the attempts to explain this phenomenon, Jegadeesh & Titman (1993) argue that the profitability of the momentum strategy is not a result of the portfolios' exposure to the usual suspects. They document that the momentum strategy is significantly profitable and attempt to explain the effect by arguing that investors buying winners and selling losers move prices away from their intrinsic values and cause prices to overreact. They also provide an alternative explanation, by arguing that investors underreact to information about short-term firm prospects but tend to overreact to long-term prospect information. Chui et al. (2010) argue that cultural differences affect the returns of the momentum strategy, and investors tend to be prone to a herding behavior in less individualistic cultures where investors are less confident about themselves and tend to follow the choices of others, driving profits for momentum strategies up. Chan et al. (1995) argue that the market anchors heavily on past trends and changes its perceptions slowly. They argue that the market takes time to adjust its beliefs and this results in the creation of intermediate horizons momentum abnormal returns.

Despite widespread presence and extensive utilization in various markets, the momentum strategy has been subject to scrutiny as some researchers argue that it possesses many inherent flaws. They have provided evidence suggesting that momentum strategies lead to formation of risk-loaded portfolios, which account for the realized returns. In other words, the momentum strategy returns could be explained by portfolios with high exposure to small capitalization or high book-to-market ratio firms. The momentum strategy in its most conventional method, sorts past losers and winners based on their 12-1 months returns. Depending on the formation period and the returns of the systematic risk factors during that period, a portfolio sorted according to past returns may unexpectedly be loaded on the usual suspects. At any given point in time, assuming that high-beta stocks performed well in the previous months, forming portfolios based on past months' performance will result in holding a high-beta portfolio. In a similar way, if low capitalization or high book-to-market ratio stocks performed well in the past, the momentum strategy will create portfolios that are severely on the Fama and French size and value factors. In other words, the conventional momentum strategy as documented by Jegadeesh and Titman (1993) tends to have significant loadings on the common risk factors, a fact that can actually explain the returns of portfolios built based on that strategy. Consequently, in times of market reversals, the profitability of the strategy will be severely impacted as the portfolios will be loaded on risk factors whose performance is reverting and worsening in the short run. In some cases, this can even lead to annihilation of any positive returns that the strategy has generated up to that point. Blitz et al. (2011) argue that momentum demonstrates a tendency to exhibit positive (negative) loadings on the common risk factors when those factors generate positive (negative) returns throughout the formation period of the momentum strategy. In view of the flaws of the conventional momentum strategy, they provide evidence that ranking stocks on their residual returns is an effective way to neutralize the dynamic factor exposures of the conventional momentum. As residual return they define the return derived from the regression of the returns on the 'β', '*value'*, and '*size' factors*. The residuals of the regression are "noise" or random fluctuations and thus the variation of returns that cannot be explained by the usual suspects will show up in the residuals of the Fama and French three-factor model. In that way, the authors isolate the part of the momentum effect that is not attributed to risk and are able to create portfolios with more stable and positive returns in the long-run.

The second anomaly whose I existence I investigate for, is the volatility anomaly, another interesting one that contradicts the classic asset pricing theories. Assuming the CAPM model is right, stocks with high(low) betas, and thus high(low) volatility, should be more attractive due to their higher(lower) expected returns in the long run. However, empirical evidence shows that high(low) beta stocks do not always overperform(underperform). On the contrary, in many literature cases, low-beta stocks are proven to overperform high-beta stocks and be more appealing for investors. This negative volatility and return relationship exhibit a volatility anomaly. The volatility strategy, which aims to extract wealth by creating portfolios based on stocks' past volatility is another strategy that has been proven to be persistent and robust over the years. Blitz & Van Vliet (2007) claim that leverage limitations and investors that overpay for risky stocks, which in turn reduces risky stocks' expected returns, make low-risk stocks more appealing and high-risk stocks less appealing. Hsu et al. (2020) argue that the volatility anomaly is most pronounced when funding liquidity risks are high. According to the authors, funding liquidity risks in a country, apply selling pressure on high-volatility stocks, giving birth to the volatility anomaly. Dutt et al. (2013) argue that low-volatility firms outside of North

America have higher operating performance and this explains why they have increased expected stock returns. Ang et al. (2006) are the first ones to identify idiosyncratic volatility, all variation in returns that is not related to the usual suspects. They argue that assuming that the Fama & French model is correct, creating portfolios based on idiosyncratic volatility of stocks should not yield excess average returns as the main Fama & French assumption is that idiosyncratic risk that is diversifiable is not priced by markets and thus does not affect expected returns. They find evidence that stocks with higher(lower) idiosyncratic volatility have lower(higher) average returns, with the effect persisting in many cases, such as bull and bear markets and recessions and expansions, raising doubts on the validity of the argument that idiosyncratic and diversifiable risk is not priced. Possible explanations for the effect include the existence of constrained investors that are not allowed to hold a fully diversified portfolio and thus they require compensation for the risk they bear. The negative relationship between total volatility and stock returns appears to be robust through different markets in the literature. However, the relationship between idiosyncratic volatility and stock returns remains yet unclear, as researchers have documented contradicting evidence about the existence of the idiosyncratic volatility anomaly.

In this research, I aim to test whether the momentum and volatility strategies can consistently yield excess returns for emerging market investors in the long run. If the momentum and the negative volatility effects are present in the emerging markets, these strategies should be able to yield arbitrary abnormal returns based on them. I focus on the ten biggest emerging economies, in terms of GDP as of 2021, according to the World Bank. In particular, I extract equity data from Datastream for China, India, Korea, Russian Federation, Brazil, Mexico, Indonesia, Turkey, Thailand, and Israel, which constitute my market. I investigate where momentum and volatility strategies are effective in this market, as well as in each of the markets individually. Based on my research purpose, I develop two main hypotheses:

1. The (residual) momentum and (residual) volatility strategies can generate abnormal returns in the emerging markets.
2. The residual momentum strategy should outperform the conventional momentum strategy due to its lower time-varying exposure to the risk factors.

I expect that if momentum and negative volatility effects are present in the market, the momentum and volatility strategies will help emerging market investors extract wealth from these markets. Moreover, I expect that the residual momentum strategy will consistently outperform the conventional momentum strategy, as I expect it to be less exposed to risk factors and thus more resistant to market crashes. In the last 22 years, we have experienced three severe market crashes, the IT bubble, the ’07 crisis, and most recently the Covid-19 crash. As my sample period covers the last two major market crashes, I consider my results to be reflective of current market conditions and intuitive about the strategy’s ability to generate positive returns that survive market turbulence.

My research contributes to the existing literature in different forms. First, I use a different approach to defining a market. By creating a market consisting of 10 countries instead of just investigating each one of them individually, I am able to identify the benefits of having access to a well-diversified world portfolio, which is more realistic of current globalization conditions. This also enables me to make an interesting comparison with the strategies effects, when I apply them to each market individually, and see how the results differ when investors do not take into account global market information, but are rather restricted and active in a specific market only. Secondly, I use a different approach than most researchers in collecting historical data for stocks. To the best of my knowledge, most researchers have been using constituent lists to extract historical data for emerging markets stock returns, while I use the entire universe of available equities available in Datastream for all equities. Thirdly, I provided updated evidence of the strategies’ efficiency, as I focus on the period from January 2000 through to December 2022, and how those perform in a period of concentrated market turbulence.

The remainder of the research is structured as follows. Section 2 provides information on available literature on momentum and volatility strategies. Section 3 describes the data and methodologies used to collect and analyze it. Section 4 analyses the methodologies for the formation of the strategies. Section 5 analyzes the results for the strategies applied on the entire investment universe, and consequently on each of the economies individually and Section 6 concludes with my conclusion.

2. Literature Review

2.1 The Momentum Strategies

The efficient market hypothesis appears to be severely challenged in the modern asset pricing literature. Asset prices systematically fail to reflect all the available information and the momentum strategies are proven to yield excess returns for investors. Most researchers present market evidence while identifying behavioral and psychological factors, such as investor overreaction or underreaction to stock news, cultural differences that lead to herding behaviors, or heavy anchoring on past trends, as the main drivers of momentum profits.

The momentum effect is present everywhere. Asness et al. (2013) provide evidence that the momentum effect is present in the US, the United Kingdom, continental Europe, and Japan, and across asset classes during the period from 1972 through to 2011. Novy-Marx (2012) provides evidence that creating portfolios based on the past 12-7 months' performances of stocks yields on average a 10% return per year from January 1927 through December 2010. Jegadeesh and Titman (1993) find evidence that the momentum effect is present in the US stock market over the period 1965 through to 1989, with the momentum strategy yielding a compounded excess return of 12.01% per year on average. The momentum strategy, however, as mentioned previously has been in many cases documented to be flawed relative to the residual momentum strategy, due to its time-varying exposure to systematic risks. Berggrun et al. (2020) find that momentum fails to yield statistically significant positive returns in Latin America both in un-adjusted and adjusted terms. If a momentum effect is present in a market, the residual momentum strategy should be able to more efficiently capture the non-market risk-related momentum effect of stocks and yield positive returns in the long run. In many researches, there is robust evidence that the residual momentum strategy outperforms relative to the momentum one. Blitz et al. (2011) compare their residual momentum strategy with the conventional[1] momentum strategy of Jegadeesh and Titman (1993) and document a lower conventional momentum strategy Sharpe ratio (Sharpe, 1964) when looking at the risk-adjusted returns. They also provide evidence that the conventional momentum strategy in the U.S. has lost its profitability in recent years, as they find evidence that it yields -8.5% negative returns per year over the period January 2000 to December 2009. On the other hand, the residual momentum

[1] Throughout the paper, I refer to the momentum strategy of Jegadeesh and Titman (1993) as conventional momentum, and the residual momentum strategy of Blitz et al. (2011) as residual momentum.

strategy which sorts stocks on their past performance after controlling for the usual suspects, generates a 4.7% return per year over the same period that the conventional momentum strategy yields losses. Qi Lin (2019) finds that the residual momentum in the Chinese market generates significant 10.584% annual returns over the period from July 1997 to December 2017 and that profits do not revert in the long run and cannot be explained by the common risk factors. Chang et al. (2018) find that the residual momentum strategy is profitable in Japan for the period from 1975 to 2011, while the profits over long-term holding periods do not reverse, unlike the conventional momentum. Ming-Yu Liu (2018) finds that the residual momentum strategy is superior to the conventional momentum strategy and yields stable returns over the period from January 1993 to December 2015 in the US as it mitigates dynamic risk factor exposure and market-wide influence. Chiao et al. (2018) present evidence that the residual momentum strategy has lower time-varying exposure to market risk and generates higher and more consistent returns over time than the conventional momentum strategy.

2.2 The Volatility Strategies

Explanations like leverage limitations, appetite for risky stocks by investors and the existence of liquidity risks have been documented by researchers as explanations of why the CAPM fails to predict stock returns. Low-volatility stocks outperforming high-volatility stocks evidence has been proven to be robust and consistent over literature.

Blitz & Van Vliet (2007) find that sorting stocks according to their past volatility and buying portfolios that go long on stocks with low historical volatility while shorting stocks with high historical volatility creates positive abnormal returns, in terms of Sharpe ratios and CAPM alphas. According to the authors, the abnormal returns are realized while the portfolios are in fact not loaded with extra exposure to the usual suspects. They document that by buying portfolios that go long on stocks with low historical volatility and short on stocks with high historical volatility, investors can yield a 12% annual excess return over the 1986-2006 period. Nartea et al. (2013) find a negative relationship between total volatility and returns in the Hong Kong market, while they find little evidence of a negative idiosyncratic volatility effect. Blitz et al. (2013) find a flat relationship between risk and return in emerging markets, showing that the CAPM fails to predict expected returns. Chang and Dong's (2006) find evidence of a negative idiosyncratic volatility effect in the Japanese market from 1975 to 2003. Annaert et al. (2022) document a negative relationship between idiosyncratic volatility and expected returns in the Euro area, of -7.27 basis points per unit of idiosyncratic volatility, with the anomaly remaining constant across subsamples.

3. Data

I download Datastream data that covers the period 31 December 1999 through to 31 December 2022. My countries of focus are China, India, Korea, Russian Federation, Brazil, Mexico, Indonesia, Turkey, Thailand, and Israel, as they constitute the 10 highest GDP countries in 2021 according to the World Bank, and are thus considered as most relevant for my research.

Most researchers use constituent lists in order to extract stock data. However, to maximize my stock coverage, instead of using constituent lists and merging them, I use the generic equity look up function of Datastream. In that way, I avoid a bias resulting from the fact that certain stocks may be included or excluded from the lists at any time, due to poor or rich performance, or increase or decrease in size Landis and Skrouras (2021). I thus utilize the "DFO Navigator" function of Datastream, and implement the below filters:

- Category: Equities
- Market: Country[2]
- Type: Equity

I include both dead and alive companies in my sample to avoid a survival bias. I download the equity list for each country and merge it into one list that constitutes my universe of research. For each company in my list, I download their static data ISIN, Company Name, and General Industry Classification Code. Next, I download the monthly observations for my period of research, of the monthly Total Return Index value (datatype RI), the month closing adjusted Price (datatype P), the monthly closing Price adjusted unpadded (datatype P#T), the monthly closing Market Value (datatype MV), and the monthly closing Unadjusted Price (datatype UP), all expressed in US dollars. I use US dollars as my universe is constituted of stocks from 10 different countries, and thus a common currency is crucial for my analysis. By default, Datastream rounds all data to the second decimal, and thus some variables expressed in US dollars, such as the Total Return Index, might not be distinct due to currency effects. In order to correct for this, I download all my data with the highest available accuracy available in

[2] As "Country" I use China, India, Korea, Russian Federation, Brazil, Mexico, Indonesia, Turkey, Thailand, and Israel for each of my list downloads. Datastream has a limit on list sizes that can be downloaded, hence a list for each country must be downloaded separately.

Datastream, which is 6 digits[3]. Finally, I download the monthly closing Price-to-book ratio (PTBV) and monthly closing Book Value (datatype WC03501) for all stocks in my universe. Consistent with the literature, I exclude Closed-end funds, Real Estate Investment Trusts (REITs), ETFs, depository receipts and unit trusts. Even though Datastream does not provide direct variables about the nature of the instruments, relevant information can be found in the Company Name variables downloaded. Consequently, I search and filter out all stocks which include "REIT", "REAL ESTATE INVESTMENT", "INVESTMENT FUND", "FUND", "ETF", "DEPOSITORY", "TRUST", "UNITS" in their Company Name. This leads to an exclusion of 91 firms in total. The total number of firms in my sample per December of each year can be found in Table A.1 in the Appendix.

Datastream data has been proven by academics to contain errors, for which I account by following the below steps. I start by winsoring the monthly Closing Unadjusted Price and monthly Total Return Index at a 99% level, as extreme outliers in these two variables will severely distort my results and conclusions. Next, I filter out all stocks without available Total Return Index data. The Total Return Index is crucial for my research as it provides a theoretical growth in the value of a shareholding over a specified period, assuming reinvesting dividends to purchase additional units of equity. I use the Total Return Index monthly difference to calculate the monthly stock returns of each stock, expressed by the following formula:

$$RI_{i,t} = \frac{RI_{i,t}}{RI_{i,t-1}} - 1 \quad (1)$$

I follow the method suggested by Landis and Skrouras (2021) to filter out extreme outliers. If the return on date *t* is greater than 100% (lower than -50%) and the return of day *t+1* is lower than -50% (greater than 100%) then both days' returns are set to missing. To further reduce instances in return data error, I follow the method of Ince and Porter (2004), and I exclude observations when returns calculated from changes in the Total Return Index have a large discrepancy with returns calculated from changes in the Unadjusted Price (datatype UP). As the authors do not clearly define what the discrepancy level shall be, I only exclude observations with more than a 5% difference to account only for the extremely high differences that would make no sense.

[3] The code I use in Datastream to extract 6 digits accuracy of data: DPL#(X(RI)~U$, 6),DPL#(X(P)~U$, 6),X(P#T)~U$,DPL#(X(MV)~U$, 6),DPL#(X(UP)~U$, 6),DPL#(X(PTBV), 6),WC03501

As a next step, I filter out observations during months when equities are no longer trading. By default, Datastream keeps reporting the last available closing Price (datatype P) when a company is "dead" and no longer trading. However, as my sample is constituted of US dollars expressed prices, all monthly closing Prices are adjusted to currency changes every month, which makes it even harder to point out stocks that are no longer traded. In order to identify stocks that are no longer traded, I filter out stocks with unavailable monthly closing Price adjusted unpadded (datatype P#T), which does no longer pad when a company is "dead". Moreover, I filter out all nonsense values, by removing observations with zero or negative values in unadjusted Prices and negative Market Capitalization values. Next, following the methodology of Landis and Skrouras (2021), and filter out stocks when their market value or book value is unavailable.

4. Methodology

In this section I analyze the methodology used for the execution of the momentum and volatility strategies. I begin by applying my methodology first on the whole universe of stocks, and then in each of the countries that constitute my universe, individually, in order to compare how the profitability of the strategies changes when an investor uses information from specific markets only. I expect that if there are momentum and negative volatility effects in the markets, then momentum and volatility strategies will prove profitable.

For the analysis of both volatility and momentum strategies, I follow the standard literature approach of portfolio sorts (see, e.g., Jegadeesh and Titman, 1993). I form *ex-ante* portfolios based on their past returns and volatility, followed by *ex-post* regressions on the market risk factor and the 3-Factor model of Fama & French (1993). In this way, I investigate whether the returns of the portfolios can be explained by a present anomaly in the market, or if they are merely compensation for the risk that is present in the portfolios. The important element that identifies the strategy's success is the alpha of the *ex-post* regressions. A positive significant regression alpha reflects a positive return generated by the strategy that is not attributed to risk factors, and thus deems that strategy profitable and successful in exploiting market anomalies to generate wealth.

I begin by creating the three risk factors namely market factor (MKTRF), small-minus-big (SMB), and high-minus-low (HML) of Fama & French (1993), that represent market return in excess of the risk-free rate, the outperformance of small-cap firms relative to large-cap firms and the outperformance of high book-to-market ratio firms relative to low book-to-market firms, respectively. The MKTRF is the monthly value-weighted (VW) excess return of stocks. For the SMB and HML factor construction I follow the methodology of French (2017) for emerging markets. At the end of every June in year *t*, stocks are sorted into deciles, according to their market capitalization and book-to-market ratios. Large stocks refer to the top 90% of the market cap in June, and small stocks are those in the bottom 10%. The breakpoints for the book-to-market ratio are determined by the 30th and 70th percentiles of the ratio. Stocks are held in the SMB and HML portfolios until the end of June of year *t+1*, when portfolios are rinsed and process is repeated. The MRKTF, SMB and HML factors are used on a first stage to derive the residual returns of stocks, and on a later stage as dependent variables for the regressions run to control for exposure of portfolios to risk and the alpha of the strategies left after adjusting for risk.

The residual return regressions are estimated on a 36-month rolling window following the methodology of Blitz et al. (2011), using the 3-Factor model:

$$r_{i,t} - R_{f,t} = a_i + \beta_1 MKRTF_t \ \ + \beta_2 SMB_t + \beta_3 HML_t + e_{i,t} \quad (2)$$

where $r_{i,t}$ represents the portfolio return and $R_{f,t}$ is the risk-free rate represented by the 1-month US treasure rate and $e_{i,t}$ represents the residual return of stocks. As prior mentioned, all random noise in portfolio returns that is not associated with risk is expected to end up in the residuals of the regression. The residualized returns are used for the formation of both residual momentum and residual volatility portfolios. In order to have a higher accuracy in the model, I only include stocks with a full history of returns over the rolling window estimation.

For the momentum portfolios, I form ex-ante portfolios based on the past performance of the stocks over the last 12 months, excluding the most recent month in order to avoid short-term reversal effects (Jegadeesh, 1990), (denoted by 12-1M). The focus on the 12-1M is the most commonly used formation period used among past research. At the end of each month, starting in December 1999 and ending in December 2022, stocks are sorted into deciles based on their past raw cumulative returns' performance, as well as their past residual cumulative returns. Consistent with the authors' work, I standardize the residual returns by their standard deviation over the last 12 months in order to generate a less noisy measure. The momentum portfolios are based on the past raw cumulative returns 12-1M performance and buy (short) the 10% best (worst) performing stocks. The residual momentum portfolios based on the past cumulative 12-1M residual returns, buy (short) the 10% of stocks with the highest (lowest) residual return performance over the formation period.

For robustness checks on the momentum strategies, I consider different formation periods for all strategies and markets. I use a *"J/1",* method of Jegadeesh and Titman (1993), with 1 month holding period, and validate the robustness of my results by confirming whether they remain unchanged for *J= [3,6,9,12]* portfolio formation periods for all strategies. In addition, I perform the execution of the strategies with alternative estimation windows using 60-month and 48-month rolling windows, keeping all other settings constant.

For the volatility portfolio formation, at the end of each month, I assign stocks into deciles according to their past three-year monthly returns' standard deviation, following the methodology of Blitz & van Vliet (2007). I create both equally and value weighted decile portfolios, that buy the top decile (henceforth denoted by D1), containing the 10% of the stocks with the lowest (residual) volatility and short the bottom decile (henceforth denoted by D10), containing the 10% of the stocks with the highest (residual) volatility. The residual volatility of stocks is derived relative to the 3-Factor model and using Equation 2, using a 36-month rolling estimation window. As a robustness check, I create portfolios based on the stocks past 48- and 60-month (residual) volatility.

In the relevant literature, penny stocks are excluded from portfolio formation in order to reduce microstructure concerns. The most common practice applied by researchers is excluding stocks during the months that their price is below 5$, 1$, or 0.5$ when working with US data. However, my universe consists of stocks from international markets and stock prices severely differ from the usual stock prices of the US markets. Evidently, a measure like that would lead to the elimination of a substantial part of my observations for particular periods, making my research infeasible. In order to avoid this issue, I follow the Landis and Skrouras (2021) method and remove stocks from my universe of month *t* when their unadjusted closing price in the previous month ends up in the lowest quartile of unadjusted closing prices.

5. Empirical Results

This section contains the empirical results of total and residual momentum and volatility strategies. I begin by investigating the results on my entire universe[4] of stocks and continue by investigating the strategies efficiency in each of the countries individually.

As mentioned earlier, I initially construct the 3-Factor model for the entire universe and then for each one of the countries individually, in order to investigate whether the strategies are efficient when using the available information from the entire universe, as well as from each of the markets individually. A summary of the MKRTF, SMB, and HML factors used for residualizing the raw stock returns and control of CAPM and 3-Factor alphas can be found in Table A.2 in the Appendix, as derived from the universe, as well as from each country individually[5]. The market factor average monthly return for the universe of stocks is 0.71%, with a *t-statistic* of 2.68, which is another indication of the high growth of wealth we have experienced over the last years in emerging markets. A quite interesting finding is that the SMB factor yields a significant negative average monthly return of -0.17%, while the HML factor yields a close to zero average monthly return. In other words, this investing universe, riskier stocks do not outperform the less risky ones. Looking at the SMB factors individually (Table A.2), the positive relation between size and stock returns is present in all countries individually, while it appears to be statistically distinguishable from zero in China, Korea, Russia, Brazil, Mexico, Indonesia, and Thailand, where big firms appear to outperform small firms. In India, Turkey, and Israel, the positive relation is still there, although it is not statistically significant. The HML factor is consistently not distinguishable from zero in most countries, except for Mexico, Indonesia, and Thailand, where it yields average monthly returns of -0.21%, -0.28%, and -0.19% respectively. The relationship between value and returns appears to be positive in all countries, although it is statistically significant in only three of them. With regards to Table A.3, the spanning test controls for the importance of factors in the explanation of market returns. According to the test, the universe MKTRF returns can be explained by the negative exposure of the market portfolio to both risk factors. The SMB and HML loadings of the factor portfolio are -3.5602 and -0.3354, with Newey & West (1986) adjusted *t-statistics* of -4.01 and -2.53 respectively. The results are consistent with a market in which there is zero or negative compensation for risk and aligned with the results of Blitz et al. (2013) that find a flat or even

[4] From this point onwards I refer to my entire universe of stocks as "universe".
[5] Henceforth I report all table results figures rounded at the second decimal

negative relationship between risk and return in emerging markets, and a market whose growth originates from the outperformance of large capitalization and high book-to-market firms.

5.1 Universe Results

I start my investigation by comparing the performance of the conventional momentum and residual momentum, using equally-weighted (EW) decile portfolios, as the standard literature approach. My main expectation related to this part is that the residual momentum will have a lower time-varying exposure to risk factors and should thus yield a higher return over time compared to the return of the conventional momentum strategy. At the same time, residual momentum should exhibit a lower volatility of returns and thus yield a higher Sharpe ratio. A summary of the results can be found in Table 5.1. Taking a closer look at the residual momentum strategy, the winner portfolio that buys the top-performing stocks exhibits the highest average positive monthly returns of 2.96%. The Winner-Loser portfolio that buys the winning portfolio and shorts the Loser portfolio, yields a significant positive average monthly return. This remains consistent when looking at the returns in excess of the risk-free rate, as well as when looking at the CAPM and 3-Factor model risk-adjusted returns, with the average monthly differences between the highest and lowest decile being 0.76%, 0.70%, and 0.64% respectively in each model, respectively.

The Winner-Loser portfolio of the conventional momentum strategy yields a relatively lower average monthly return of 0.56%, with a lower statistical significance. The strategy outcome remains positive as well, when controlling for CAPM and 3-Factor model risk-adjusted returns, yielding 0.60% and 0.58% average monthly returns respectively. The residual momentum strategy keeps outperforming its peer, even when adjusting for risk. The standard deviation, a measure of volatility, of the strategy is 0.046, yielding a Sharpe ratio of 0.165, relative to 0.130 of the conventional momentum strategy. Consequently, the residual momentum strategy outperforms the conventional momentum strategy in terms of alphas, both before and after controlling for the risk factors, indicating that the strategy in its initial form is more efficient in the long run.

To control for the robustness of the results, I first use alternative estimation windows, of 48 months and 60 months for the residual returns. This leaves me with available observations from January 2005 to December 2022 and January 2006 to December 2022, as the rolling windows require a returns history of 4 and 5 years respectively. I thus compare the efficiency of the strategies based on their common portfolio returns availability. The results can be found in Table

A.4 in the Appendix. The evidence is consistent with an outperformance of the residual momentum strategy, relative to the conventional momentum strategy for the 48-month estimation window, during the period January 2005 to December 2022. The monthly average residual momentum returns of the Winner-Loser portfolio are 1.15% with a *t-statistic* of 3.60. Looking at the 60-month estimation window results, for the period January 2006 to December 2022, the residual momentum strategy yields an average monthly excess return of 1.32% with a *t-statistic* of 3.56. The results indicate that the residual momentum strategy consistently outperforms the momentum strategy when using alternative estimation windows for the returns residuals. This can be possibly explained by the increase in market observations used to residualize returns. Using more observations to filter the raw past performance of stocks, provides a more accurate measure for the residual returns that allows the model to, more efficiently, disentangle the market movement effects on the stock prices from the stock performance part that is not market-related. Moreover, we observe that the returns of the residual momentum strategy increase monotonically as we allow the model to use a higher number of market observations to derive residuals and sort portfolios, highlighting the importance of a sufficient number of market data when hedging-out risk.

Moving forward, I employ a *"J/1"* of Jegadeesh & Titman (1993) to test the profitability of the strategies using different formation periods for the construction of the portfolios. The results in Table A.5 in the Appendix, indicate that the past 3,6 and 9-month residual performance of stocks is a poor indicator of future performance. In particular, both the 3-month and the 6-month formation periods yield a -0.03% average monthly return, with *t-statistics* -0.21 and -0.22 respectively. Using the 9-month past residual performance to form portfolios, the strategy yields a positive 0.05% average monthly return with a *t-statistic* of 0.34, indicating that the result is not distinguishable from zero. For the conventional momentum strategy, the past 3 and 6-month raw returns performance are also poor predictors of future performance, with the portfolios formed based on them yielding -0.04% and 0.51% average monthly returns with *t-statistics* of -0.13 and 1.63. On the other hand, forming conventional momentum portfolios based on the past 9-month raw returns performance, yields an average monthly return of 0.81%, with a high *t-statistic* of 2.76.

As presented in Table 5.2, I find evidence that the conventional momentum portfolio has a higher exposure to the risk factors relative to the residual momentum portfolio. The Winner-Loser conventional momentum portfolio exhibits MKRTF, SMB and HML factor exposures of 0.59, 3.08 and -0.92 respectively. Even though the results are statistically insignificant, the signs indicate the conventional momentum strategy creates portfolios with a higher correlation with the risk factors, as the residual momentum strategy creates more neutrally positioned portfolios. The residual momentum portfolios exhibit MKRTF, SMB and HML factor exposures of -0.48, -0.43 and -0.40 respectively. The residual momentum appears to be less prone to market movements, which makes it more stable over the long-run and more resistant to high market turbulence. The evidences lead to an acceptance of the initial hypothesis, that the outperformance of the residual momentum strategy stems from a lower exposure to the risk factors.

To test for the existence of realistic investing opportunities using the momentum strategies, I also create value-weighted (VW) portfolios. This method takes into account the market capitalization of stocks, as lower market cap stocks tend to be less liquid and less available for purchases, a fact that sometimes makes the EQ strategy not feasible. In this method, higher market capitalization stocks have more weight, and portfolios are more reflective of the available portfolios for purchase. The results in Table 5.3, indicate that the VW strategies still generate positive returns, even though not statistically significant. Both strategies' returns are contracted relative to the EW portfolios, with the residual momentum strategy yields a 0.51% monthly excess return with a *t-statistic* of 1.38, while the conventional momentum strategy yields a 0.46% monthly return with a *t-statistic* of 0.65. Even though the results are not statistically significant, the positive signs on the returns indicates that there are possibly realistic positive returns opportunities in the universe. The residual momentum once again exhibits higher risk-adjusted risk returns, with a Sharpe ratio of 0.092, more than double of that of the momentum strategy, that exhibits a Sharpe ratio of 0.044.

The results in Table 5.4, are indicative of the residual momentum's strategy capability to create more risk-neutral portfolios than its peer strategy, in VW portfolios as well. The residual momentum MKRTF, SMB and HML coefficients are -0.12, -0.88 and 0.00, while the conventional momentum strategy exhibits coefficients of 0.54, 0.50 and 2.19 respectively. The results are consistent with existence of a momentum effect in the entire universe of stocks, indicating that the emerging markets are characterized by herding behavior and investors that anchor on past trends, following the choices of other investors as they have less belief in their own abilities, driving up the momentum strategies' profits. The momentum strategies evidence showcases profitable residual momentum and conventional momentum strategies in the entire universe of stocks. The residual momentum strategy consistently outperforms the conventional momentum strategy when using a 12-1M formation period for the portfolio construction, with its strong performance growing when different rolling estimation windows for the residual returns, and exhibits a higher Sharpe ratio.

Table 5.1: (Residual) Momentum Strategies Performance for EW portfolios

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0220***	0.0126***	0.0121***	0.0151***	0.0050**	0.0040
	(4.99)	(6.00)	(5.66)	(3.07)	(1.99)	(1.53)
2	0.0209***	0.0109***	0.0089***	0.0185***	0.0091***	0.0073***
	(4.42)	(4.81)	(3.87)	(4.17)	(4.22)	(3.41)
3	0.0220***	0.0129***	0.0119***	0.0235***	0.0144***	0.0118***
	(4.89)	(5.26)	(4.72)	(5.20)	(5.72)	(4.70)
5	0.0020	0.0012	0.0004	0.0220***	0.0145***	0.0141***
	(1.64)	(1.13)	(0.44)	(5.55)	(5.64)	(5.22)
6	-0.0006	-0.0009	-0.0012	0.0224***	0.0140***	0.0128***
	(1.80)	(1.53)	(1.05)	(6.14)	(8.20)	(7.29)
8	0.0238***	0.0188***	0.0139***	0.0251***	0.0166***	0.0129***
	(5.78)	(5.49)	(4.75)	(6.03)	(6.04)	(7.27)
9	0.0276***	0.0181***	0.0168***	0.0199***	0.0108***	0.0082***
	(6.01)	(7.44)	(6.94)	(4.65)	(5.80)	(4.55)
Winner	0.0296***	0.0196***	0.0185***	0.0207***	0.0109***	0.0098***
	(5.78)	(6.76)	(6.51)	(4.64)	(5.77)	(5.21)
Winner-Loser	0.0076**	0.0070*	0.0064**	0.0056*	0.0060**	0.0058*
	(2.49)	(1.93)	(2.28)	(1.94)	(2.14)	(1.91)
Standard deviation	0.046			0.043		
Sharpe Ratio	0.165			0.130		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table 5.2: (Residual) Momentum Strategies Factor Coefficients for EW portfolios

Decile	Residual Momentum			Conventional Momentum		
	MKRTF	SMB	HML	MKRTF	SMB	HML
Loser	1.9039***	2.2213**	0.6970	1.4665***	-0.4794	1.4799*
	(7.54)	(2.42)	(1.34)	(2.96)	(-0.26)	(1.68)
2	1.7716***	1.0048	1.5225*	2.2803***	3.2332**	1.1767
	(5.11)	(0.83)	(1.94)	(5.18)	(1.99)	(1.61)
3	1.8953***	1.4957	1.2593**	2.7022***	4.3617***	2.0789***
	(5.47)	(1.20)	(2.04)	(6.36)	(2.81)	(2.83)
4	2.6523***	5.1029***	2.3356***	1.1283**	0.7080	-0.6895
	(5.82)	(3.10)	(3.23)	(2.06)	(0.36)	(-0.71)
5	0.2709	-1.3211*	2.5225***	1.8768***	3.4549*	-0.4357
	(1.23)	(-1.74)	(6.13)	(3.27)	(1.72)	(-0.55)
6	0.0490	-0.7051*	1.0044***	2.3979***	4.4594***	0.6398
	(0.45)	(-1.69)	(2.70)	(5.24)	(2.77)	(0.92)
7	1.5362***	2.7528	2.1365***	3.3003***	7.5859***	0.4952
	(3.15)	(1.50)	(2.66)	(8.96)	(5.63)	(0.88)
8	1.5479***	-0.2432	1.9453***	4.0182***	9.8301***	1.8726***
	(4.13)	(-0.18)	(3.37)	(9.77)	(6.40)	(2.85)
9	1.8038***	1.5008	0.9258	3.2351***	7.0711***	1.1386**
	(4.06)	(0.96)	(1.40)	(11.63)	(6.70)	(2.05)
Winner	1.8005***	1.7817	0.2910	2.0570***	2.6014**	0.5644
	(3.97)	(1.12)	(0.39)	(6.54)	(2.33)	(1.12)
Winner-Loser	-0.1034	-0.4395	-0.4060	0.5905	3.0807	-0.9155
	(-0.27)	(-0.31)	(-0.50)	(1.10)	(1.54)	(-0.99)

This table displays the risk factor coefficients of equally-weighted decile portfolios of the Residual and Conventional Momentum for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table 5.3: (Residual) Momentum Strategies Performance for VW portfolios

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0048*	0.0020	0.0007	0.0158***	0.0059	0.0059
	(1.70)	(0.74)	(0.26)	(2.63)	(1.28)	(1.22)
2	0.0089**	0.0046	0.0042	0.0132***	0.0065	0.0063
	(2.39)	(1.39)	(1.24)	(2.79)	(1.60)	(1.42)
3	0.0089	0.0021	0.0013	0.0181***	0.0123***	0.0117***
	(1.65)	(0.43)	(0.24)	(3.84)	(3.10)	(2.89)
4	0.0195***	0.0104*	0.0068	0.0030	-0.0027	-0.0033
	(2.84)	(1.74)	(1.20)	(0.75)	(-0.70)	(-0.96)
5	0.0013	-0.0010	-0.0028	0.0100**	0.0041	0.0060*
	(0.36)	(-0.26)	(-0.72)	(2.25)	(1.00)	(1.69)
6	0.0005*	0.0004*	0.0004	0.0198***	0.0156***	0.0157***
	(1.78)	(1.67)	(1.51)	(3.41)	(2.87)	(2.63)
7	0.0030***	0.0026***	0.0029**	0.0146***	0.0088*	0.0049
	(2.90)	(2.97)	(2.40)	(2.97)	(1.85)	(1.10)
8	0.0063***	0.0036*	0.0039*	0.0194***	0.0121**	0.0091*
	(2.60)	(1.70)	(1.82)	(3.55)	(2.43)	(1.88)
9	0.0031	-0.0019	-0.0008	0.0104*	0.0027	0.0006
	(0.91)	(-0.56)	(-0.28)	(1.97)	(0.61)	(0.14)
Winner	0.0099***	0.0061**	0.0051*	0.0203***	0.0097*	0.0079
	(3.12)	(2.04)	(1.70)	(3.03)	(1.73)	(1.36)
Winner-Loser	0.0051	0.0042	0.0044	0.0046	0.0039	0.0019
	(1.38)	(1.09)	(1.12)	(0.65)	(0.56)	(0.26)
Standard deviation	0.0557			0.1046		
Sharpe Ratio	0.092			0.044		

This table displays the performance of value-weighted decile portfolios of the Residual momentum and Conventional Momentum for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table 5.4: (Residual) Momentum Strategies Factor Coefficients for VW portfolios

Decile	Residual Momentum			Conventional Momentum		
	MKRTF	SMB	HML	MKRTF	SMB	HML
Loser	1.1361***	2.4931*	0.8806*	1.1238	-0.4273	0.0516
	(2.92)	(1.71)	(1.86)	(1.44)	(-0.15)	(0.04)
2	0.9300*	1.4557	0.0740	1.2294*	1.5763	-0.1055
	(1.85)	(0.82)	(0.13)	(1.74)	(0.64)	(-0.10)
3	2.7293**	7.6604*	-0.8756	0.7523*	-0.3358	0.8223
	(2.33)	(1.90)	(-0.74)	(1.83)	(-0.21)	(0.77)
4	3.9546***	9.6218***	1.9769	0.7265	-0.3840	0.7969
	(4.61)	(3.22)	(1.51)	(0.83)	(-0.13)	(0.49)
5	0.5199	-0.3681	2.2778***	0.0640	-1.4192	-2.0124*
	(1.57)	(-0.26)	(2.66)	(0.09)	(-0.58)	(-1.71)
6	-0.0067	-0.0641	0.0571	0.9729**	2.1103	-0.7333
	(-0.41)	(-0.59)	(0.85)	(2.00)	(1.01)	(-0.55)
7	-0.0189	-0.0621	-0.3513	2.9578***	6.7991***	3.0047***
	(-0.11)	(-0.11)	(-0.94)	(4.09)	(2.76)	(3.17)
8	0.2156	-0.2926	-0.3282	3.3910***	8.5958***	1.4249
	(0.74)	(-0.27)	(-0.49)	(5.54)	(3.94)	(1.40)
9	-0.4823	-4.0263**	-0.2487	2.3383***	4.4924*	1.3372
	(-0.91)	(-2.03)	(-0.25)	(4.40)	(1.96)	(1.03)
Winner	1.0186**	1.6104	0.8827*	1.6632**	0.0709	2.2372*
	(2.16)	(0.93)	(1.67)	(2.18)	(0.02)	(1.79)
Winner-Loser	-0.1175	-0.8827	0.0020	0.5394	0.4982	2.1856
	(-0.18)	(-0.38)	(0.00)	(0.63)	(0.15)	(1.30)

This table displays the risk factor coefficients of value-weighted decile portfolios of the Residual and Conventional Momentum for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Next, I investigate the effectiveness of the volatility strategies for the entire universe of stocks, beginning with the equal-weighted portfolios. The results in Table 5.5 indicate the presence of a volatility effect. Stocks are sorted into deciles according to their past 3-year residual returns volatility and their past 3-year total volatility. Stocks with the highest residual and total volatility consistently outperform stocks with the lowest volatility in the long run. Looking at the residual volatility strategy, the most volatile stocks in the 10^{th} decile, generate an average monthly return of 3.06% monthly with a *t-statistic* of 5.37, outperforming the least volatile stocks in the 1^{st} decile that generate an average monthly return of 2.02% with a *t-statistic* of 5.13. The D1-D10 portfolio that buys the least volatile stocks and shorts the most volatile ones yields an average monthly return of -1.05% with a *t-statistic* of -2.46. The loss from the strategy is persistent when risk-adjusting using both the CAPM and the 3-Factor model, with average monthly returns of -1.13% and -1.38% respectively.

By ranking stocks based on their total volatility, the volatility effect in the investing universe becomes more pronounced, with the D1-D10 portfolio yielding monthly average returns of -1.61%, -1.51%, and -1.68% with *t-statistics* of -3.98, -3.56 and -3.88, for returns over the risk-free rate and risk-adjusted returns using the CAPM and 3-Factor model respectively.

The results remain unchanged when sorting stocks and creating portfolios using the volatility of residual returns over the past 48 and 60 months. Results are in Table A.6 in the Appendix, showing -0.67% and -0.89% average monthly returns with *t-statistics* of -0.81 and -0.76, for the residual volatility strategy based on the volatility of the past 48 and 60 months respectively. The total volatility strategy also fails to generate positive returns, yielding -0.75% and -0.79% monthly average returns with *t-statistics* of -0.96 and -0.75. Evidently, both volatility strategies fail to generate positive abnormal returns for investors in the entire universe of stocks. In Table 5.6 is documented the exposure of both residual and total volatility portfolios to the risk factors. The residual volatility portfolio, has lower MKRTF and HML coefficients than the total volatility strategy, while its exposure to the SMB factor is almost identical to the total volatility's one, in absolute terms.

Moving to the value-weighted portfolios results in Table 5.7, that residual volatility strategy consistently yields negative abnormal returns, while the total volatility strategy generates returns close and not statistically distinguishable than zero. The residual volatility strategy yields a -0.66% monthly return with a *t-statistic* of -1.67, while the total volatility strategy yields a 0.03% monthly return with a *t-statistic* of 0.08. The slightly positive sign of returns in the total volatility value-weighted portfolio indicates that there might be realistic investing strategy opportunities based on least volatile stocks, that will yield positive returns. The VW strategy increases the portfolio weight on higher market capitalization stocks who tend to be less volatility over time, which can explain why the total volatility strategy yields slightly positive, instead of negative returns, when using this method.

Looking at the factor coefficients of the VW portfolios in Table 5.8, both strategies have a positive loading on the MKRTF factor, with coefficients of 0.55 and 0.46 respectively. The SMB coefficients of residual and total volatility are 2.02 and 2.11, with *t-statistics* of 1.14 and 1.06 respectively, which is an indication of the portfolios' positive loading in small firms. The relative outperformance of the total volatility strategy in the VW portfolios can be possibly explained by the significant difference in HML loadings of the two strategies. The residual volatility strategy exhibits a significant positive loading on the factor, with a coefficient of 1.45 and a *t-statistic* of 2.02, while the total volatility strategy has a negative factor loading with a coefficient of -0.22 and a *t-statistic* of -0.29. This result indicates that the residual volatility strategy loads on high book-to-market stocks which are more volatility over time, while the total volatility strategy "prefers" low book-to-market stocks which are empirically proven to be more stable over time.

The results lead to a rejection of the hypothesis that the volatility strategies can generate significant positive abnormal returns for investors. However, there is weak evidence that creating portfolios based on stocks past total with more weight to higher market capitalization stocks might generate positive abnormal returns.

Table 5.5: Residual Volatility and Total Volatility Performance for EW portfolios

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0202***	0.0125***	0.0119***	0.0134***	0.0085***	0.0090***
	(5.13)	(4.51)	(4.32)	(3.99)	(2.83)	(3.10)
2	0.0187***	0.0111***	0.0112***	0.0177***	0.0106***	0.0108***
	(4.54)	(3.66)	(3.73)	(4.36)	(3.33)	(3.36)
3	0.0194***	0.0118***	0.0119***	0.0212***	0.0132***	0.0133***
	(4.66)	(3.85)	(3.89)	(4.72)	(3.75)	(3.82)
4	0.0210***	0.0133***	0.0134***	0.0262***	0.0176***	0.0180***
	(4.84)	(3.87)	(4.04)	(5.45)	(4.80)	(4.93)
5	0.0202***	0.0130***	0.0132***	0.0243***	0.0153***	0.0151***
	(4.67)	(3.76)	(3.80)	(5.16)	(4.50)	(4.48)
6	0.0229***	0.0150***	0.0154***	0.0255***	0.0172***	0.0172***
	(5.00)	(4.09)	(4.17)	(5.33)	(4.63)	(4.59)
7	0.0265***	0.0187***	0.0193***	0.0289***	0.0211***	0.0213***
	(5.33)	(4.53)	(4.60)	(5.74)	(5.14)	(5.00)
8	0.0301***	0.0228***	0.0230***	0.0320***	0.0251***	0.0255***
	(5.91)	(5.02)	(5.00)	(6.24)	(5.44)	(5.47)
9	0.0327***	0.0252***	0.0259***	0.0271***	0.0206***	0.0214***
	(6.00)	(5.34)	(5.38)	(5.14)	(4.20)	(4.31)
10	0.0306***	0.0238***	0.0257***	0.0296***	0.0235***	0.0258***
	(5.37)	(4.37)	(4.78)	(5.12)	(4.22)	(4.65)
D1-D10	-0.0105**	-0.0113**	-0.0138***	-0.0161***	-0.0151***	-0.0168***
	(-2.46)	(-2.54)	(-3.13)	(-3.98)	(-3.56)	(-3.88)

This table displays the performance equally-weighted decile portfolios of the Residual volatility and Conventional Volatility for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table 5.6: Residual Volatility and Total Volatility Factor Coefficients for EW portfolios

Decile	Residual Volatility			Total Volatility		
	MKRTF	SMB	HML	MKRTF	SMB	HML
1	1.6286***	1.6586	0.7990	0.6165**	-1.3272	0.7835
	(5.80)	(1.62)	(1.64)	(2.17)	(-1.25)	(1.44)
2	1.5264***	1.1512	0.6232	1.1035***	-0.2965	0.5405
	(5.10)	(1.07)	(1.06)	(3.27)	(-0.24)	(0.86)
3	1.6249***	1.3003	0.6114	1.6170***	1.5916	0.1256
	(5.81)	(1.26)	(1.14)	(4.37)	(1.19)	(0.19)
4	1.8894***	1.9859*	0.8294	1.7768***	1.8244	0.0966
	(5.93)	(1.76)	(1.32)	(4.53)	(1.31)	(0.15)
5	2.0516***	2.3481**	0.8578	1.9075***	2.1941	0.0567
	(6.20)	(1.98)	(1.38)	(4.98)	(1.63)	(0.09)
6	1.7979***	1.5438	0.4131	1.9853***	2.1492*	0.3373
	(4.80)	(1.16)	(0.63)	(6.29)	(1.94)	(0.59)
7	1.8366***	1.2402	0.8872	1.9048***	1.1951	1.1788*
	(4.77)	(0.92)	(1.48)	(5.65)	(1.02)	(1.91)
8	1.6417***	0.5924	0.6851	1.7033***	0.1131	1.2609*
	(3.97)	(0.41)	(0.95)	(4.30)	(0.08)	(1.71)
9	1.8469***	0.6912	1.5366**	1.8421***	0.6405	1.6437**
	(3.91)	(0.42)	(2.20)	(4.04)	(0.40)	(2.06)
10	1.8923***	0.8138	1.5565*	1.6545***	-0.4965	2.2485**
	(3.50)	(0.43)	(1.69)	(3.25)	(-0.27)	(2.48)
D1-D10	-0.2637	0.8448	-0.7575	-1.0379***	-0.8307	-1.4650*
	(-0.60)	(0.54)	(-0.92)	(-2.65)	(-0.55)	(-1.89)

This table displays the risk factor coefficients of equally-weighted decile portfolios of the Residual volatility and Total Volatility for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table 5.5: Residual Volatility and Total Volatility Performance for VW portfolios

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0016	-0.0007	-0.0016	0.0048***	0.0027	0.0029
	(1.03)	(-0.45)	(-0.89)	(2.68)	(1.64)	(1.51)
2	0.0041	0.0002	-0.0005	0.0042**	0.0014	0.0013
	(1.60)	(0.09)	(-0.22)	(2.08)	(0.76)	(0.64)
3	0.0080**	0.0034	0.0037	0.0024	-0.0010	-0.0005
	(2.05)	(0.97)	(1.12)	(1.01)	(-0.45)	(-0.20)
4	0.0067***	0.0032	0.0027	0.0065**	0.0031	0.0035
	(2.76)	(1.60)	(1.30)	(2.27)	(1.14)	(1.28)
5	0.0043*	0.0014	0.0006	0.0103***	0.0071**	0.0076**
	(1.74)	(0.65)	(0.25)	(3.14)	(2.21)	(2.05)
6	0.0076**	0.0028	0.0035	0.0105***	0.0070**	0.0073**
	(2.32)	(1.15)	(1.15)	(2.96)	(2.24)	(2.16)
7	0.0059*	0.0023	0.0004	0.0029	0.0002	-0.0014
	(1.75)	(0.65)	(0.12)	(0.87)	(0.06)	(-0.43)
8	0.0069**	0.0037	0.0040	0.0069**	0.0036	0.0039
	(2.52)	(1.33)	(1.31)	(2.47)	(1.46)	(1.44)
9	0.0047**	0.0023	0.0018	0.0034	0.0007	0.0004
	(2.25)	(1.24)	(0.93)	(1.47)	(0.30)	(0.17)
10	0.0083**	0.0042	0.0052	0.0045	0.0018	0.0021
	(2.05)	(0.99)	(1.16)	(1.58)	(0.67)	(0.80)
D1-D10	-0.0066*	-0.0049	-0.0068	0.0003	0.0009	0.0007
	(-1.67)	(-1.11)	(-1.44)	(0.08)	(0.29)	(0.23)

This table displays the performance value-weighted decile portfolios of the Residual volatility and Conventional Volatility for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table 5.6: Residual Volatility and Total Volatility Factor Coefficients for VW portfolios

Decile	Residual Volatility			Total Volatility		
	MKRTF	SMB	HML	MKRTF	SMB	HML
1	0.4859***	0.4469	0.7522*	0.2206	0.0686	-0.1817
	(2.86)	(0.66)	(1.79)	(1.17)	(0.09)	(-0.43)
2	0.9739***	1.8621	0.3914	0.3145	-0.0233	0.0921
	(2.74)	(1.42)	(0.65)	(1.44)	(-0.03)	(0.21)
3	0.8671**	1.6972	-0.5880	0.3621	0.2421	-0.6090
	(2.37)	(1.19)	(-0.97)	(1.02)	(0.20)	(-0.95)
4	1.1378***	2.8038***	0.0600	0.4760	0.6660	-0.5431
	(4.08)	(2.71)	(0.15)	(1.60)	(0.58)	(-0.85)
5	0.8421***	1.7002	0.5524*	0.7059	1.7942	-0.8658
	(2.90)	(1.59)	(1.74)	(1.65)	(1.27)	(-1.10)
6	-0.0519	-2.0419	-0.3267	0.5749	0.9847	-0.4972
	(-0.09)	(-1.03)	(-0.34)	(1.37)	(0.64)	(-0.73)
7	1.4584*	3.3341	1.1983*	0.9948**	1.9347	1.2818***
	(1.94)	(1.26)	(1.66)	(2.06)	(1.04)	(2.63)
8	0.5996	1.1584	-0.4536	0.1557	-0.7162	-0.1418
	(1.63)	(0.92)	(-0.80)	(0.38)	(-0.47)	(-0.24)
9	0.5256*	0.7723	0.3637	0.3131	-0.1114	0.2805
	(1.94)	(0.77)	(0.99)	(1.03)	(-0.10)	(0.58)
10	-0.0639	-1.5811	-0.6979	-0.2345	-2.0424	0.0366
	(-0.13)	(-0.92)	(-0.99)	(-0.51)	(-1.14)	(0.06)
D1-D10	0.5498	2.0279	1.4502**	0.4552	2.1111	-0.2182
`	(1.11)	(1.14)	(2.02)	(0.90)	(1.06)	(-0.29)

This table displays the risk factor coefficients of value-weighted decile portfolios of the Residual volatility and Total Volatility for the entire universe of stocks for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

5.2 Country-Specific Results

In this section, I investigate the efficiency of the strategies in each country individually. For each country in my sample, I construct the Fama & French risk factors from the country specific stocks and follow the rest of the methodology as described in Section 4.

5.2.1 China

The advantages of residual momentum relative to conventional momentum are more pronounced in the Chinese market. The results for the momentum strategies are in Table A.8 in the Appendix.

The residual momentum strategy generates an average monthly excess return of 0.52% monthly with a t-statistic of 2.49 and a Sharpe ratio of 0.167. The alpha generated is still present and significant after the risk control, as the monthly average excess return is 0.47% and 0.49% with t-statistics of 2.41 and 2.47 when controlling for the CAPM and the 3-Factor model respectively. The conventional momentum strategy, on the other hand, generates a -0.43% average monthly excess return with a t-statistic of -1.23. The results remain consistent over the robustness checks, as the residual momentum yields positive monthly average excess returns of 0.34% and 0.52% when using different regression rolling windows of 48 and 60 months for the estimation of residuals, respectively. Using different formation periods of 3,6 and 9 months of past residual and raw returns (Table A.5), the residual momentum generates 0.24%, 0.09%, and 0.12% average monthly excess returns respectively, even though they are not statistically significant. The conventional momentum, on the other hand, yields statistically significant -0.66% and statistically insignificant -0.16% and 0.36% average monthly excess returns when using the same settings. The results are consistent with those of Qi Lin (2019) who finds that the residual momentum strategy in the Chinese market yields significant positive returns and outperforms the conventional momentum strategy that yields non-distinguishable from zero returns.

Moving to Table A.9, there is evidence of a negative volatility effect. Less volatile stocks appear to slightly outperform the most volatility ones, even though the evidence is not compelling. The average monthly excess returns of the residual volatility strategy are 0.01% monthly and the risk-adjusted returns are 0.32% and 0.25% when controlling for the CAPM and 3-Factor model respectively. The total volatility strategy generates an average excess monthly return of 0.36%, however not statistically significant. By sorting stocks based on their past 48- and 60-month residual and raw returns volatility, the results remain unchanged, as documented in Table A.7.

5.2.2 India

Moving to the Indian market, the results in Table A.10 in the Appendix document the existence of a momentum effect. The residual momentum strategy generates an average monthly excess return of 0.5%, with a t-statistic of 2.50. The average monthly excess return remains at 0.48% and 0.50% when controlling for the CAPM and the 3-Factor model, with t-statistics of 2.50, 2.61 and 2.78 respectively, indicating that risk factors add no explanatory power to the returns of the Winner-Loser portfolio. In other words, the residual momentum strategy successfully generates positive abnormal returns, without loading on any extra risk. The effect is persistent when using 48- and 60-month rolling window regressions to obtain the residual returns, with average monthly excess returns being 0.54% and 0.62% respectively.

The conventional momentum strategy generates an average monthly excess return of 0.69% with a t-statistic of 2.01. The returns of the strategy are persistent when controlling for the CAPM and the 3-Factor model as explanatory variables. Using alternative formation period windows of 3,6 and 9 months, the past residual returns fail to predict future returns (Table A.5). The average monthly excess returns fluctuate from -0.13% to 0.04% while being statistically insignificant. On the other hand, the past 3,6, and 9-month raw returns appear to be good predictors of future returns, as the conventional momentum strategy sorting stocks based on them, generates average monthly excess returns of 0.92% 0.85%, and 0.68%.

Despite the outperformance of conventional momentum in the Indian market, the residual momentum exhibits a lower standard deviation of 0.029 relative to its peer, documenting a standard deviation of 0.056. Hence, the residual momentum has a higher Sharpe ratio of 0.168, while the conventional momentum exhibits a Sharpe ratio of 0.134. This risk-adjusted higher metric is an indication of the residual momentum having a lower time-varying exposure to the common risk factors, which explains its lower volatility.

With regards to Table A.11, both the residual and the total volatility strategies, fail to generate any excess returns for the investors, as they generate -1.84% and -1.80% average monthly excess returns, with high statistical significance, respectively. The results remain consistent when sorting portfolios based on the past 48- and 60-month residual and total volatility.

5.2.3 Korea

The results for the momentum strategies in the Korean market are in Table A.12. This market evidence is also consistent with the existence of a momentum effect. Both strategies generate significant positive abnormal returns, with the residual momentum strategy overperforming. The residual momentum strategy generates and average monthly excess return of 1.05% with a t-statistic of 4.45. The strategy's profits survive the risk controls using the CAPM and 3-Factor model, with the regressions' alphas being 1.03% and 0.99% respectively. Using alternative estimation windows for the regression residuals, the strategy consistently generates significant returns of 0.76% and 0.80% monthly, as seen in Table A.6. The strategy's outperformance persists when using alternative 3,6, and 9-month past residual returns to sort the portfolios, yielding significant returns of 0.34%, 0.53% and 0.80% monthly, respectively (Table A.5). The conventional momentum yields a return of 0.67%, with a t-statistic of 2.10. The returns are 0.68% and 0.57% monthly when controlling for the CAPM and the 3-Factor model. Sorting portfolios based on past 3 months raw returns generates an insignificant monthly return of 0.18%. However, sorting portfolios based on past 6 months raw returns generates 0.46% monthly return with a t-statistic of 1.67. The 9-month raw returns are even more robust predictors of future performance, as the strategy yields a monthly return of 0.65% when sorting portfolios based on that. Comparing the two strategies, the residual momentum is outperforming the conventional momentum strategy, yielding a higher average return and almost a double in size Sharpe ratio of 0.297, relative to a Sharpe ratio of 0.139 of the conventional momentum strategy. Consequently, the residual momentum strategy is successful in outperforming both in total return terms, as well as in risk-adjusted terms in the Korean market.

Moving to Table A.13, the Korean market also exhibits a volatility effect, as both residual and total volatility strategies fail to yield positive returns. More volatility stocks outperform less volatiles ones, and thus the residual volatility strategy generates a -2.09% monthly return with a t-statistic of -5.05, while the total volatility strategy generates a -1.51% monthly return with a t-statistic of -2.91. The strategies' profitability remains negative when sorting portfolios based on their past 48- and 60-month volatility (Table A.7).

5.2.4 Russia

The momentum effects in Table A.14 indicate that the both momentum strategies yield positive returns. The residual momentum strategy yields positive but statistically insignificant monthly returns of 0.24%. The risk-adjusted returns are 0.22% and 0.08% monthly when controlling for the common risk factors, with t-statistics 0.39 and 0.14 respectively. The statistically weak residual momentum effect is persistent when using alternative regression windows of 48 and 60 months for the residuals, yielding monthly returns of 0.33% and 1.35% monthly, with t-statistics of 0.41 and 1.77 respectively (Table A.6). Using the past 3,6 and 9-month residual returns to form portfolios, the residual momentum strategy fails to generate profits statistically significant from zero, yielding -0.68%, 0.26% and 0.01% monthly returns respectively. The conventional momentum on the other hand exhibits strong performance, yielding a monthly return of 1.26% with a t- statistic of 2.19. The returns remain persistent when controlling for risk using the CAPM and the 3-Factor model, generating returns of 1.31% and 1% monthly respectively. The positive conventional momentum effect remains when using alternative past raw returns performance to form portfolios, however, only the 6-month past performance yields statistically significant returns of 1.54% monthly. The residual momentum strategy fails to outperform the conventional momentum strategy in this market. A possible explanation could be the inefficiency of the Fama and French factors constructed from Russian market data to efficiently reflect the market risk. If the risk factors used to derive the residuals of the regressions are not appropriate, the residuals do not provide an improved momentum metric and the strategy is not efficient.

Moving to Table A.15, the Russian market provides indications of a weak negative volatility effect, similar to the one documented in the Chinese market. Both the residual and total volatility strategies yield positive monthly returns, although they are not statistically distinguishable from zero. The residual volatility strategy yields a 0.07% monthly return, with a t-statistic of 0.06, while the total volatility strategy yields a 0.79% monthly return with a t-statistic of 0.78. Both strategies' returns exhibit positive statistically insignificant risk-adjusted returns. By sorting portfolios based on stocks past 48- and 60-months volatility, both strategies yield slightly positive or even negative insignificant monthly returns.

5.2.5 Brazil

The results in Table A.16 are consistent with the existence of a momentum effect in the Brazilian market. The residual momentum yields a 042% monthly return, although not statistically different that zero. Controlling for risk using the CAPM and the 3-Factor model, the monthly returns remain positive at 0.46% and 0.48% monthly return and t-statistics of 1.24 and 1.32 respectively. Using alternative regression estimation windows for the residuals and past returns formation periods, the residual momentum strategy persistently yields non distinguishable from zero monthly returns, fluctuating from -0.15% to 0.36% monthly (Table A.6). The conventional momentum strategy yields a 0.95% monthly return on average, with a t-statistic of 2.13. The return remains positive and significant when controlling for risk, the CAPM and 3-Factor alphas being 0.0102 and 0.0113 with t-statistics 2.33 and 2.62. respectively.

Next, Table A.17 documents a positive volatility effect in the market, with both residual volatility and total volatility strategies yielding significant negative returns. The residual volatility strategy generates a -2.76% monthly return with a t-statistic of -3.28. The total volatility yields a more negative return of -4% monthly with a t-statistic of -2.76. The results for both strategies remain negative and significant when sorting portfolios based on past 48- and 60-month residual and total volatility of stocks.

5.2.6 Mexico

The residual momentum strategy evidence is consistent of an outperformance of the conventional momentum strategy in the market of Mexico (Table A.18). The monthly residual momentum return generated is 0.26% with a t-statistic of 0.62. The results remain positive after controlling for the risk factors using the CAPM and the 3-Factor model, with the strategy yielding 0.21% and 0.19% monthly returns respectively, although statistically insignificant. Using alternative regression windows, the residual estimation, the monthly returns are slightly negative, and once again not statistically significant from zero. The conventional momentum strategy on the other hand, yields negative monthly returns of -0.40% with a t-statistic of -0.87, that remain negative after the CAPM and 3-Factor model controls. Even though the results from both strategies are statistically insignificant, the outperformance of the residual momentum strategy is still present, due to its ability to reduce the time-varying exposure of portfolios to the common risk factors. Using alternative portfolio formation periods of 3,6 and 9 months, the past residual returns appear to be good predictors of future returns, with the 3 different strategy settings yielding 0.57%, 0.34% and 0.47% monthly returns respectively (Table A.5). However, only the 3-month formation period strategy has a significant positive return at 10% level, with the other two strategies exhibiting t-statistics of 0.92 and 1.36. The momentum strategy consistently yields either slightly positive or even negative, statistically insignificant monthly returns, when using past raw 3,6 or 9 months returns to sort portfolios. The evidence about the existence of a momentum effect in the market is weak. However, the residual momentum strategy's positive returns might be an indication that the effect is still present.

The volatility strategies fail to generate positive returns in the market of Mexico as well with the residual volatility and the total volatility strategies yielding -2.37% and -179% monthly returns with t-statistics of -2.45 and -1.83 respectively (Table A.19). The results remain unchanged when using portfolio sorts based on past 48- and 60-month residual and total volatility (Table A.7)

5.2.7 Indonesia

As documented in Table A.19, the residual momentum strategy in Indonesia generates a statistically significant monthly return of 1.79% with a t-statistic of 2.93. The positive returns are present even after risk adjusting using the CAPM the 3-Factor model, yielding 1.78% and 1.68% monthly returns with t-statistics 2.71 and 2.19 respectively. Using 48- and 60-month alternative residual returns estimation windows, the strategy consistently yields statistically significant positive returns of 1.54% and 1.15% monthly, respectively (Table A.6). The strategy's efficiency proves to be robust, as using 3,6 and 9 months past residual returns to sort portfolios, yields return of 0.77%, 1.10% and 1.70% monthly, with t-statistics of 2.00, 3.12, and 4.79 respectively. The residual momentum strategy's superior efficiency becomes even more pronounced when comparing it with its peer conventional momentum strategy, that yields a -0.89% monthly return, statistically significant at 10% level. The past 3,6- and 9-month raw returns are poor predictors of future performance, with portfolios sorted based on them, yielding 0.57%, 0.17% and -0.60% monthly returns, not statistically significant from zero (Table A.5). Both residual and total volatility strategies once again fail to generate positive returns for investors, yielding statistically significant monthly returns of -3.78% and -3.47% respectively (Table A.21). The negative profitability of the strategy remains persistent when sorting portfolios according to past 48 and 90 month past residual and total volatility with returns fluctuating from -1.21% to -3.90% monthly.

5.2.8 Turkey

The residual momentum strategy is the outperformer again in the market of Turkey in terms of total return, yielding a monthly return of 0.82% with a t-statistic of 1.72 (Table A.22). The strategy's profitability does not stem from exposure of portfolios to risk factors, as the CAPM and the 3-Factor model risk-adjusted monthly returns are 0.82% and 0.78% with statistics of 1.77 and 1.66 respectively. However, using alternative estimation windows to derive the residual returns, raises doubts about the robustness of the strategy, as the monthly returns are not statistically distinguishable from zero (Table A.6). The past 3,6 and 9-month residual returns, as seen in Table A.5, are poor predictors of future performance, with portfolios sorted based on them yielding, non-significantly different than zero, -0.19%, 0.21% and 0.26%

monthly returns respectively. The conventional yields a 0.20% monthly return with a t-statistic of 0.54. The strategy's profitability, although positive, is not statistically different that zero. By sorting portfolios based on their past 3,6 and 9-month returns, the conventional momentum yields 0.79%, 0.19% and -0.20% monthly returns with t-statistics 2.03, 0.45 and -0.54 respectively. The evidence is consistent with the existence of a momentum effect in the Turkish market, although somehow weak. The residual momentum strategy in its original 12-1M setting, manages to generate wealth from the momentum effect in the market and outperforms the conventional momentum strategy, but the evidence of a consistent outperformance when using alternative settings is weak.

Both volatility strategies fail to generate positive returns for investors in this market. The residual volatility strategy generates a -1.68% monthly return with a t-statistic of -3.16 (Table A.23). The negative returns are persistent when sorting portfolios based on their past 48- and 60-month residual returns volatility, as seen in Table A.7. The total volatility strategy yields a -1.22% monthly return, although not statistically different than zero, with the robustness checks indicating a poor performance of the strategy for alternative sorting methods as well.

5.2.9 Thailand

In the Thailand market, both momentum strategies generate positive returns in view of a momentum effect in the market. As seen in Table A.24 residual momentum yields a monthly return of 0.43%, however not significant. The insignificant monthly returns are 0.33% and 0.23% when controlling for the CAPM and the 3-Factor model respectively. An interesting finding is the ability of the residual momentum to generate better and statistically significant results when using longer estimation windows for the residuals. In particular, using 48 months regression windows and sorting stocks based on their 12-1M residual performance, yields a monthly return of 0.55% with a t-statistic of 1.84. The monthly return and t-statistic of the strategy increases even further when using a 60-month regression window, yielding monthly returns of 0.72% with a t-statistic of 2.12 (Table A.7). This result is an indication that allowing for regressions to account for a longer time exposure of returns to the market, the model is able to capture the origin of returns not attributed to market movements, more efficiently. Moreover, the past residual 3,6 and 9-month performance of stocks, are evidently good predictors of future performance, with strategies sorting portfolios based on the yielding 0.45%, 0.37% and 0.54% monthly returns with t-statistics 2.29, 1.98, and 2.90 respectively, as documented in Table A.5. Despite the promising residual momentum results, the conventional momentum remains undefeated in this market. The strategy yields monthly returns of 0.45%, statistically significant at 10% level. In addition, the positive monthly returns are still present after controlling with the CAPM and the 3-Factor model. Finally, the 3,6 and 9-month past raw returns successfully predict future performance, with the strategies yielding 1.15%, 0.96% and 0.70% monthly returns respectively.

Residual and total volatility strategies fail to generate positive returns in this market. The residual volatility strategy generates -1.75% monthly returns with a t-statistic of -2.66, while the total volatility strategy generates monthly returns of -2.59% with a t-statistic of -2.59, as presented in Table A.25. The negative results from strategies remain persistent when sorting stocks based on 48- and 60-month past volatility of residual and total returns, indicating a positive volatility effect in the market, and thus an inefficiency of the strategy.

5.2.10 Israel

The momentum effect is also present in the Israel market, as indicated in Table A.26. The residual momentum strategy, however, fails to outperform the conventional momentum strategy, yielding an insignificant monthly return of 0.23%. The strategy's low performance is persistent when using alternative estimation windows for the residuals, as well as when using the past 3,6 and 9-month performance to sort portfolios. On the other hand, the conventional momentum strategy yields a monthly return of 0.82% with a t-statistic of 2.24. After controlling with the CAPM and the 3-Factor model, the strategy generates statistically significant results at 1% level of 0.98% and 1.13% monthly. However, the past 3,6 and 9-month raw returns are evidently poor predictors of future performance, with the portfolios created based on them yielding non-distinguishable from zero returns (Table A.5).

Both volatility strategies generate statistically significant negative returns. The residual volatility strategy yields a -1.33% monthly return with a t-statistic of -2.44, while the total volatility strategy yields a -1.37% monthly return with a t-statistic of -2.21. The negative strategies performance is persistent when sorting portfolios based on their past 48- and 60-month volatility (Table A.6).

6. Conclusion

In this research, I investigate the effectiveness of (residual) momentum and volatility strategies in the emerging markets. The importance of my research stems from the rapid growth of the emerging markets and the rapid internalization that makes investing in these markets more appealing over time, while they also expand opportunities for portfolios diversification. My results contribute to the existing literature as I find that hedging-out the time-varying exposure to systematic risk in an emerging markets universe that offers diversification opportunities, investors can enjoy a higher and more stable over-time profitability. I follow an innovative way of defining the market and I find evidence of the existence of a momentum effect in these markets in that period, potentially stemming from herding and anchoring behaviors in those markets where investors have less information and tend to follow the choices of others. I test the momentum strategy in its conventional form as first described by Jegadeesh & Titman (1993) and compare it with the residual momentum strategy of Blitz et al. (2011) and I find that the residual momentum strategy outperforms the conventional momentum of strategy in this entire universe of stocks, when using the past 12-1M residual(raw) returns, yielding an average monthly excess return of 0.76% over the period January 2004 to December 2022. Moreover, I find evidence that the strategy's outperformance if not attributed to risk factors, and that the strategy is feasible as the effect is persistent in value-weighted portfolios. The evidence is consistent with my hypothesis that due to lower time-varying exposure to common risk factors, the residual momentum is more stable in the long run, hence the strategy yields a higher Sharpe ratio of 0.165, relative to the conventional momentum strategy's ratio of 0.130. I also investigate the strategies' effect when using available information from each of the markets individually, and find evidence that residual momentum strategy outperforms in the markets of China, Korea, Mexico, Indonesia and Turkey, while it underperforms relative to the conventional momentum strategy in the markets of India, Brazil, Thailand and Israel. Even though my method is different, my results are consistent with existing literature, such as Qi Lin (2019), who finds evidence of residual momentum outperformance in the market of China. Finally, I also investigate the existence of a negative volatility effect and the effectiveness of strategies based on residual and total volatility of stocks. I find strong evidence of a volatility effect in all of the markets constituting my universe, as well as in each of the markets individually, with the exception of the Chinese market, where less volatile stocks showcase a weak, statistically insignificant, outperformance of 0.36% relative to more volatility stocks.

Further studies including a bigger sample of markets would add greater value, by highlighting the benefits of diversification even further. As global markets become more and more integrated and thus correlated, with spillover effects from crises transmitting to other markets in a swifter manner, risk factors and strategies' efficiency and benefits would be even more reliable and reflective of current market conditions.

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A Tables and Figures

Table A.1: Number of firms

Year	China	India	Korea	Russia	Brazil	Mexico	Indonesia	Turkey	Thailand	Israel	Universe
1999	941	2117	644	18	456	157	257	247	367	356	5560
2000	1081	2207	736	23	448	152	273	277	359	381	5937
2001	1158	2256	832	27	429	143	304	276	364	389	6178
2002	1226	2289	922	28	415	135	319	276	379	391	6380
2003	1290	2356	973	32	388	124	322	274	402	389	6550
2004	1378	2435	1018	35	379	121	324	286	439	401	6816
2005	1381	2938	1080	48	365	122	324	291	485	417	7451
2006	1429	3085	1136	65	363	123	330	306	506	444	7787
2007	1552	3263	1204	88	391	120	353	310	516	491	8288
2008	1627	3373	1244	123	374	119	375	308	522	491	8556
2009	1722	3432	1305	133	354	118	389	309	537	490	8789
2010	2066	3603	1386	138	353	124	411	328	546	504	9459
2011	2342	3732	1458	146	337	122	431	352	555	501	9976
2012	2493	3851	1485	154	315	125	451	381	573	468	10296
2013	2487	3951	1544	157	307	123	477	397	604	444	10491
2014	2611	4091	1618	157	292	124	500	395	638	421	10847
2015	2825	4286	1726	163	281	129	516	392	667	406	11391
2016	3049	4458	1799	165	267	129	532	389	683	403	11874
2017	3480	4627	1886	171	246	132	562	375	713	404	12596
2018	3576	4671	1983	171	243	131	614	377	728	400	12894
2019	3751	4721	2073	172	231	131	663	378	755	395	13270
2020	4073	4714	2148	174	244	129	708	372	772	401	13735
2021	4544	4810	2254	177	271	126	761	421	804	476	14644
2022	4814	4915	2369	178	253	124	819	457	840	486	15255
All	56896	86181	34823	2743	8002	3083	11015	8174	13754	10349	235020
Mean	2371	3591	1451	114	333	128	459	341	573	431	9793

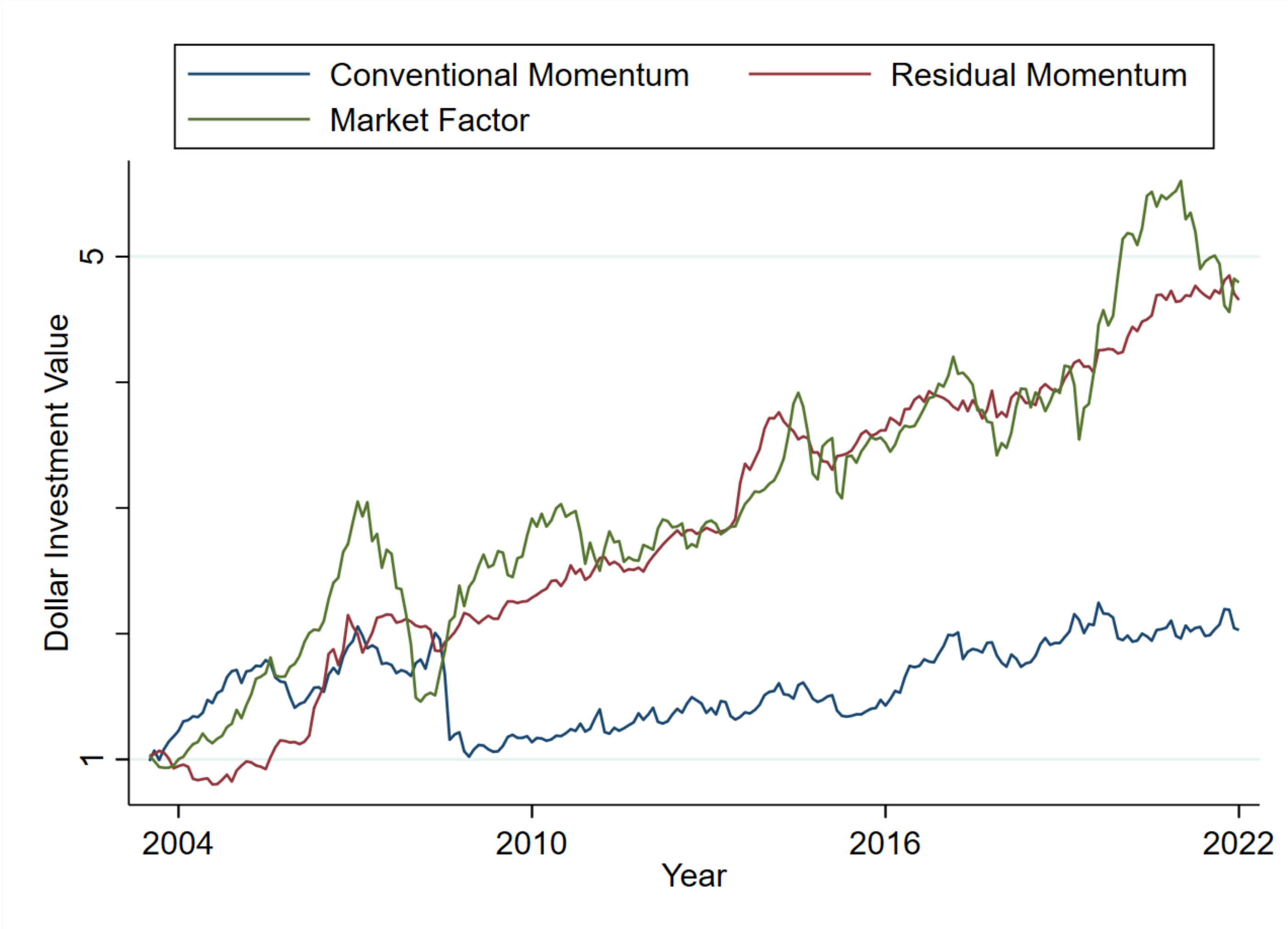
This tables displays the number of firms in the entire sample at December of each year, downloaded from Datastream using the methodology presented in Section 3.

Table A.2: Fama and French Factors per Country

Market	MKRTF	SMB	HML
China	0.0077***	-0.0010*	0.0004
	(2.83)	(-1.93)	(1.28)
India	0.0092**	-0.0039	-0.0024
	(2.21)	(-1.08)	(-1.05)
Korea	0.0079*	-0.0021*	-0.0010
	(1.89)	(-1.69)	(-0.97)
Russia	0.0114***	-0.0025**	-0.0004
	-2.74	(-2.13)	(-0.77)
Brazil	0.0095**	-0.0021**	-0.0004
	(2.47)	(-2.13)	(-0.69)
Mexico	0.0093***	-0.0020**	-0.0021**
	(2.76)	(-2.46)	(-2.34)
Indonesia	0.0112***	-0.0030***	-0.0028**
	(2.90)	(-2.80)	(-2.46)
Turkey	0.0085	-0.0020	-0.0001
	(1.56)	(-1.32)	(-0.09)
Thailand	0.0089***	-0.0024***	-0.0019**
	(2.72)	(-2.65)	(-2.37)
Israel	0.0062**	-0.0013	-0.0003
	-2.13	(-1.61)	(-0.48)
Universe	0.0071***	-0.0017**	-0.0000
	(2.68)	(-2.37)	(-0.00)

This table displays the Fama and French risk factors, constructed by information available on each of the markets. MKTRF is the monthly value-weighted (VW) excess return of stocks. SMB and HML are the size and value factors constructed using the method of French (2017) for emerging markets as described in Section 4. Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Figure A.1: The Conventional Momentum Vs the Residual Momentum Strategy



This figure displays the cumulative return performance of the EW Residual Momentum Strategy Vs the Conventional Momentum Strategy, in the entire universe of stocks for the period January 2004 through to December 2022. The strategies are applied as described in Section 4.

Table A.3: Factor spanning test: Universe

	Intercept	MKRTF	SMB	HML
MKRTF	0.0012**		-3.5602***	-0.3354**
	(2.47)		(-4.01)	(-2.53)
SMB	0.0001	-0.2513***		0.0498
	(1.09)	(-3.26)		(1.17)
HML	0.0009***	-0.0881**	0.1852	
	(3.64)	(-2.55)	(1.22)	

This table displays the regressions results using two factors to explain the return of the third one. MKTRF is the monthly value-weighted (VW) excess return of stocks. SMB and HML are the size and value factors constructed using the method of French (2017) for emerging markets as described in Section 4. Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.4: Residual momentum returns using alternative 48- and 60-month estimation windows

Loser	2	3	4	5	6	7	8	9	Winner	Winner-Loser
Panel A: January 2005 to December 2022										
0.0195***	0.0206***	0.0230***	0.0076***	0.0032**	0.0021*	0.0054**	0.0176***	0.0301***	0.0310***	0.0115***
(4.29)	(4.15)	(5.23)	(2.96)	(2.08)	(1.92)	(2.21)	(4.11)	(5.93)	(5.87)	(3.60)
Panel B: January 2006 to December 2022										
0.0177***	0.0214***	0.0238***	0.0061*	0.0014	0.0059***	0.0081***	0.0264***	0.0334***	0.0308***	0.0132***
(3.77)	(4.08)	(4.69)	(1.92)	(1.56)	(3.07)	(3.01)	(3.51)	(5.47)	(5.32)	(3.56)

This table displays the performance of the Residual momentum strategy in the entire universe of stocks, using alternative 48- and 60-month regression windows to estimate the residual returns with the Fama and French 3-Factor model. Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.5: (Residual) Momentum Strategies with alternative portfolio formation periods

Market	Residual Momentum			Conventional Momentum		
	J=3	J=6	J=9	J=3	J=6	J=9
China	0.0024	0.0009	0.0012	-0.0066**	-0.0016	-0.0036
	(1.45)	(0.58)	(0.68)	(-2.44)	(-0.54)	(-1.13)
India	-0.0013	-0.0007	0.0004	0.0092***	0.0085***	0.0068**
	(-0.82)	(-0.43)	(0.24)	(4.25)	(3.24)	(2.10)
Korea	0.0034**	0.0053***	0.0080***	0.0018	0.0046*	0.0065**
	(2.08)	(3.07)	(4.82)	(0.65)	(1.67)	(2.07)
Russia	-0.0068	0.0026	0.0001	0.0048	0.0154**	0.0010
	(-1.37)	(0.53)	(0.01)	(0.78)	(2.55)	(0.09)
Brazil	0.0020	0.0022	0.0036	0.0030	0.0083*	0.0043
	(0.80)	(0.84)	(1.48)	(0.84)	(1.79)	(0.96)
Mexico	0.0057*	0.0034	0.0047	0.0048	0.0003	-0.0018
	(1.73)	(0.92)	(1.36)	(1.22)	(0.07)	(-0.43)
Indonesia	0.0077**	0.0110***	0.0170***	0.0057	0.0017	-0.0060
	(2.00)	(3.12)	(4.79)	(1.54)	(0.44)	(-0.99)
Turkey	-0.0019	0.0021	0.0026	0.0079**	0.0019	-0.0020
	(-0.38)	(0.51)	(0.64)	(2.03)	(0.45)	(-0.54)
Thailand	0.0045**	0.0037**	0.0054***	0.0115***	0.0096***	0.0070**
	(2.29)	(1.98)	(2.90)	(4.64)	(4.02)	(2.47)
Israel	-0.0025	-0.0025	-0.0018	-0.0011	0.0006	0.0030
	(-1.20)	(-0.97)	(-0.84)	(-0.35)	(0.18)	(0.79)
Universe	-0.0003	-0.0003	0.0005	-0.0004	0.0051	0.0081***
	(-0.21)	(-0.22)	(0.34)	(-0.13)	(1.63)	(2.76)

This table displays the momentum strategies performance in the entire universe of stocks, using alternative formation period windows of 3,6 and 9 months, as described in Section 4. Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.6: Residual and Total Volatility Strategies in the Universe using Alternative Formation Windows

Decile	Residual Volatility		Total Volatility	
	(1)	(1)	(1)	(2)
1	0.0182**	0.0185*	0.0093	0.0056
	(2.58)	(2.00)	(1.58)	(0.69)
2	0.0127*	0.0143	0.0127	0.0273**
	(1.73)	(1.31)	(1.65)	(2.30)
3	0.0163**	0.0172*	0.0212**	0.0339**
	(2.08)	(1.72)	(2.20)	(2.46)
4	0.0276***	0.0249**	0.0284***	0.0364***
	(3.47)	(2.04)	(3.39)	(2.73)
5	0.0190**	0.0338**	0.0297***	0.0324***
	(2.13)	(2.52)	(3.16)	(2.75)
6	0.0293***	0.0364**	0.0261***	0.0227*
	(3.27)	(2.64)	(2.89)	(1.85)
7	0.0326***	0.0163	0.0295***	0.0351**
	(2.94)	(1.12)	(3.06)	(2.56)
8	0.0245**	0.0341**	0.0241**	0.0178
	(2.48)	(2.35)	(2.36)	(1.28)
9	0.0342***	0.0424**	0.0263**	0.0227
	(3.16)	(2.49)	(2.45)	(1.66)
10	0.0248**	0.0274*	0.0169	0.0135
	(2.12)	(1.70)	(1.65)	(0.93)
D1-D10	-0.0067	-0.0089	-0.0075	-0.0079
	(-0.81)	(-0.76)	(-0.96)	(-0.75)

This table displays the performance of the Residual and Total Volatility for the entire universe of stocks using alternative formation windows based on stocks past 48 (1) and 60 month (2) residual and total volatility. Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.7: Residual and Total Volatility Strategies in different markets using Alternative Formation Windows

Market	Residual Volatility		Total Volatility	
	(1)	(2)	(1)	(2)
China	0.0009	-0.0014	0.0040	0.0035
	(0.28)	(-0.38)	(1.03)	(0.85)
India	-0.0160***	-0.0096**	-0.0114**	-0.0092
	(-4.37)	(-2.22)	(-2.48)	(-1.63)
Korea	-0.0197***	-0.0157***	-0.0102**	-0.0139***
	(-4.54)	(-3.51)	(-2.08)	(-2.80)
Russia	0.0050	-0.0066	-0.0127	-0.0141
	(0.55)	(-0.66)	(-0.92)	(-0.98)
Brazil	-0.0296**	-0.0243*	-0.0276	-0.0624**
	(-2.38)	(-1.88)	(-1.48)	(-2.39)
Mexico	-0.0155**	-0.0035	-0.0071	-0.0215**
	(-2.39)	(-0.55)	(-0.87)	(-2.30)
Indonesia	-0.0390***	-0.0322***	-0.0259**	-0.0121
	(-5.12)	(-5.20)	(-2.37)	(-0.97)
Turkey	-0.0190***	-0.0188***	-0.0124	-0.0238**
	(-3.23)	(-3.17)	(-1.35)	(-2.39)
Thailand	-0.0144**	-0.0207***	-0.0224**	-0.0176*
	(-2.40)	(-2.65)	(-2.35)	(-1.92)
Israel	-0.0120**	-0.0127**	-0.0155*	-0.0076
	(-2.06)	(-2.03)	(-1.91)	(-1.23)

This table displays the performance of the Residual and Total Volatility for different markets using alternative formation windows based on stocks past 48- (1) and 60-month (2) residual and total volatility. Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.8: (Residual) Momentum Strategies Performance in China

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0248***	0.0142***	0.0131***	0.0234***	0.0121**	0.0113**
	(4.04)	(3.00)	(3.27)	(3.48)	(2.32)	(2.38)
2	0.0241***	0.0144***	0.0136***	0.0291***	0.0176***	0.0152***
	(4.07)	(2.95)	(3.29)	(4.22)	(3.29)	(3.33)
3	0.0196***	0.0112***	0.0101**	0.0315***	0.0210***	0.0188***
	(3.77)	(2.61)	(2.48)	(4.72)	(3.89)	(4.23)
4	0.0133***	0.0085**	0.0042	0.0327***	0.0215***	0.0196***
	(3.21)	(2.21)	(1.27)	(4.85)	(4.09)	(4.47)
5	0.0097***	0.0079***	0.0069***	0.0331***	0.0226***	0.0203***
	(3.09)	(2.87)	(2.68)	(5.05)	(4.18)	(4.59)
6	0.0074**	0.0061*	0.0051	0.0321***	0.0215***	0.0197***
	(2.25)	(1.96)	(1.65)	(5.01)	(4.28)	(5.00)
7	0.0157***	0.0128***	0.0117***	0.0310***	0.0201***	0.0183***
	(3.66)	(3.22)	(2.87)	(4.79)	(3.92)	(4.67)
8	0.0259***	0.0193***	0.0164***	0.0267***	0.0161***	0.0142***
	(4.88)	(4.07)	(3.55)	(4.35)	(3.32)	(4.05)
9	0.0284***	0.0185***	0.0169***	0.0229***	0.0122**	0.0112***
	(4.69)	(3.81)	(3.94)	(3.73)	(2.55)	(3.22)
Winner	0.0299***	0.0190***	0.0179***	0.0191***	0.0081*	0.0083**
	(4.77)	(3.89)	(4.40)	(3.18)	(1.82)	(2.51)
Winner-Loser	0.0052**	0.0047**	0.0049**	-0.0043	-0.0040	-0.0031
	(2.49)	(2.41)	(2.47)	(-1.23)	(-1.15)	(-0.86)
Standard deviation	0.0311			0.0525		
Sharpe Ratio	0.167			-0.08		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Chinese market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.9: Residual Volatility and Total Volatility Performance in China

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0248***	0.0121***	0.0099***	0.0244***	0.0133***	0.0116***
	(4.58)	(4.86)	(4.28)	(5.01)	(5.41)	(4.91)
2	0.0270***	0.0140***	0.0117***	0.0291***	0.0162***	0.0139***
	(4.72)	(4.53)	(4.18)	(5.01)	(5.15)	(4.83)
3	0.0299***	0.0162***	0.0143***	0.0303***	0.0173***	0.0152***
	(5.11)	(5.73)	(5.47)	(5.21)	(5.44)	(5.27)
4	0.0294***	0.0154***	0.0129***	0.0305***	0.0174***	0.0152***
	(4.94)	(5.60)	(5.38)	(5.22)	(5.51)	(5.07)
5	0.0276***	0.0140***	0.0121***	0.0296***	0.0153***	0.0138***
	(4.57)	(4.39)	(4.18)	(4.78)	(5.24)	(4.98)
6	0.0294***	0.0152***	0.0132***	0.0352***	0.0213***	0.0198***
	(4.85)	(5.33)	(4.98)	(5.69)	(6.31)	(6.35)
7	0.0337***	0.0196***	0.0180***	0.0310***	0.0161***	0.0141***
	(5.51)	(6.21)	(6.47)	(4.83)	(4.87)	(4.65)
8	0.0293***	0.0153***	0.0133***	0.0285***	0.0135***	0.0116***
	(4.78)	(4.79)	(4.64)	(4.46)	(4.24)	(4.06)
9	0.0266***	0.0122***	0.0100***	0.0290***	0.0136***	0.0121***
	(4.23)	(3.59)	(3.25)	(4.34)	(4.30)	(4.05)
10	0.0246***	0.0089***	0.0074**	0.0208***	0.0054	0.0031
	(3.61)	(2.83)	(2.51)	(3.07)	(1.56)	(1.00)
D1-D10	0.0001	0.0032	0.0025	0.0036	0.0080**	0.0085***
	(0.05)	(1.28)	(0.96)	(0.99)	(2.57)	(2.75)
Standard deviation	0.0447			0.0563		
Sharpe Ratio	0.0032			0.0638		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Chinese market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.10: (Residual) Momentum Strategies Performance in India

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0212***	0.0083***	0.0068***	0.0219***	0.0069**	0.0052*
	(3.41)	(3.25)	(3.06)	(2.96)	(2.07)	(1.76)
2	0.0213***	0.0070**	0.0057**	0.0127**	0.0075*	0.0070*
	(3.09)	(2.57)	(2.26)	(2.24)	(1.93)	(1.94)
3	0.0215***	0.0077***	0.0062**	0.0114**	0.0024	0.0030
	(3.24)	(2.82)	(2.53)	(2.19)	(0.71)	(0.95)
4	0.0211***	0.0074***	0.0061**	0.0136***	0.0027	0.0041
	(3.21)	(2.82)	(2.55)	(2.64)	(0.76)	(1.25)
5	0.0098**	0.0042	0.0022	0.0215***	0.0060	0.0067*
	(2.30)	(1.18)	(0.70)	(4.25)	(1.58)	(1.84)
6	0.0072**	0.0043	0.0031	0.0196***	0.0141***	0.0134***
	(2.37)	(1.51)	(1.16)	(2.98)	(3.63)	(3.57)
7	0.0113**	0.0054	0.0058	0.0177***	0.0113***	0.0094***
	(2.47)	(1.36)	(1.51)	(3.79)	(2.95)	(2.91)
8	0.0240***	0.0108***	0.0095***	0.0211***	0.0144***	0.0115***
	(3.71)	(3.88)	(3.73)	(4.26)	(3.66)	(3.58)
9	0.0281***	0.0145***	0.0130***	0.0246***	0.0155***	0.0125***
	(4.32)	(5.56)	(5.71)	(4.53)	(4.66)	(4.70)
Winner	0.0261***	0.0131***	0.0118***	0.0288***	0.0167***	0.0149***
	(4.16)	(5.08)	(5.11)	(4.91)	(6.58)	(6.84)
Winner-Loser	0.0050**	0.0048***	0.0050***	0.0069**	0.0098***	0.0097***
	(2.50)	(2.61)	(2.78)	(2.01)	(3.25)	(3.23)
Standard deviation	0.0298			0.0516		
Sharpe Ratio	0.168			0.134		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the India market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.11: Residual Volatility and Total Volatility Performance in India

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0187***	0.0045**	0.0038**	0.0185***	0.0068***	0.0063***
	(3.43)	(2.44)	(2.11)	(4.12)	(4.39)	(4.13)
2	0.0224***	0.0074***	0.0065***	0.0224***	0.0078***	0.0069***
	(3.84)	(3.41)	(3.12)	(3.98)	(3.98)	(3.68)
3	0.0231***	0.0070***	0.0059***	0.0252***	0.0099***	0.0087***
	(3.69)	(3.06)	(2.71)	(4.23)	(4.36)	(4.12)
4	0.0256***	0.0096***	0.0086***	0.0274***	0.0110***	0.0097***
	(4.11)	(4.11)	(3.84)	(4.21)	(4.07)	(3.79)
5	0.0240***	0.0080***	0.0069***	0.0285***	0.0116***	0.0099***
	(3.76)	(2.93)	(2.72)	(4.18)	(3.78)	(3.60)
6	0.0272***	0.0105***	0.0090***	0.0283***	0.0108***	0.0096***
	(4.12)	(3.87)	(3.65)	(4.03)	(3.57)	(3.39)
7	0.0301***	0.0126***	0.0105***	0.0305***	0.0122***	0.0108***
	(4.22)	(3.85)	(3.66)	(4.15)	(3.85)	(3.71)
8	0.0318***	0.0150***	0.0132***	0.0325***	0.0143***	0.0122***
	(4.58)	(4.53)	(4.35)	(4.33)	(4.01)	(3.75)
9	0.0356***	0.0180***	0.0158***	0.0320***	0.0139***	0.0119***
	(4.91)	(5.14)	(5.12)	(4.27)	(3.77)	(3.54)
10	0.0371***	0.0195***	0.0168***	0.0365***	0.0171***	0.0145***
	(4.95)	(5.01)	(5.06)	(4.47)	(4.08)	(3.90)
D1-D10	-0.0184***	-0.0150***	-0.0130***	-0.0180***	-0.0103**	-0.0082**
	(-5.02)	(-4.50)	(-4.45)	(-3.69)	(-2.59)	(-2.26)
Standard deviation	0.0566			0.0756		
Sharpe Ratio	-0.3247			-0.2386		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the India market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.12:(Residual) Momentum Strategies Performance in Korea

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0181***	0.0096***	0.0070***	0.0141**	0.0051*	0.0026
	(3.39)	(4.40)	(3.90)	(2.41)	(1.84)	(1.06)
2	0.0206***	0.0116***	0.0093***	0.0241***	0.0149***	0.0125***
	(3.67)	(5.16)	(4.75)	(4.26)	(5.24)	(4.86)
3	0.0230***	0.0141***	0.0116***	0.0250***	0.0156***	0.0129***
	(4.16)	(6.27)	(6.20)	(4.61)	(5.50)	(5.44)
4	0.0212***	0.0126***	0.0103***	0.0240***	0.0165***	0.0144***
	(3.89)	(5.35)	(5.02)	(4.37)	(6.87)	(6.73)
5	0.0187***	0.0099***	0.0076***	0.0275***	0.0157***	0.0132***
	(3.42)	(4.53)	(3.93)	(4.97)	(5.75)	(5.83)
6	0.0243***	0.0154***	0.0128***	0.0239***	0.0189***	0.0164***
	(4.36)	(6.66)	(6.72)	(4.07)	(7.53)	(7.51)
7	0.0205***	0.0116***	0.0091***	0.0284***	0.0196***	0.0170***
	(3.69)	(5.03)	(4.58)	(5.05)	(7.83)	(7.85)
8	0.0256***	0.0168***	0.0142***	0.0288***	0.0203***	0.0174***
	(4.61)	(7.18)	(7.16)	(5.30)	(8.02)	(8.30)
9	0.0262***	0.0172***	0.0148***	0.0253***	0.0167***	0.0133***
	(4.63)	(7.22)	(7.23)	(4.56)	(6.43)	(6.71)
Winner	0.0286***	0.0199***	0.0169***	0.0209***	0.0118***	0.0083***
	(5.03)	(7.22)	(7.26)	(3.54)	(4.24)	(4.02)
Winner-Loser	0.0105***	0.0103***	0.0099***	0.0067**	0.0068**	0.0057*
	(4.45)	(4.50)	(4.28)	(2.10)	(2.17)	(1.87)
Standard deviation	0.0354			0.0481		
Sharpe Ratio	0.297			0.139		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Korea market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.13: Residual Volatility and Total Volatility Performance in Korea

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0174***	0.0088***	0.0075***	0.0141***	0.0063***	0.0054***
	(3.97)	(5.00)	(4.62)	(3.49)	(3.63)	(3.27)
2	0.0175***	0.0083***	0.0068***	0.0199***	0.0107***	0.0094***
	(3.72)	(4.66)	(4.26)	(4.24)	(5.70)	(5.43)
3	0.0196***	0.0096***	0.0078***	0.0168***	0.0070***	0.0053***
	(3.84)	(5.01)	(4.58)	(3.36)	(3.61)	(3.09)
4	0.0207***	0.0106***	0.0085***	0.0220***	0.0113***	0.0093***
	(4.01)	(5.19)	(4.91)	(3.98)	(4.91)	(4.89)
5	0.0235***	0.0132***	0.0107***	0.0218***	0.0112***	0.0091***
	(4.36)	(5.61)	(5.67)	(3.96)	(4.79)	(4.45)
6	0.0237***	0.0128***	0.0103***	0.0266***	0.0156***	0.0134***
	(4.20)	(5.57)	(5.57)	(4.63)	(6.02)	(5.78)
7	0.0266***	0.0159***	0.0129***	0.0284***	0.0170***	0.0144***
	(4.70)	(6.11)	(6.75)	(4.56)	(5.34)	(5.13)
8	0.0262***	0.0153***	0.0123***	0.0312***	0.0198***	0.0170***
	(4.46)	(5.26)	(5.24)	(5.01)	(6.33)	(6.07)
9	0.0297***	0.0187***	0.0152***	0.0316***	0.0198***	0.0165***
	(4.91)	(6.11)	(6.66)	(4.75)	(5.48)	(5.56)
10	0.0383***	0.0271***	0.0235***	0.0292***	0.0180***	0.0137***
	(5.75)	(6.56)	(6.82)	(4.08)	(3.79)	(3.45)
D1-D10	-0.0209***	-0.0182***	-0.0160***	-0.0151***	-0.0117**	-0.0084**
	(-5.05)	(-4.59)	(-4.44)	(-2.91)	(-2.41)	(-1.98)
Standard deviation	0.0640			0.0803		
Sharpe Ratio	-0.3265			-0.1883		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Korean market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.14:(Residual) Momentum Strategies Performance in Russia

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0161**	0.0057	0.0036	0.0046	-0.0069	-0.0083*
	(2.13)	(1.37)	(0.89)	(0.53)	(-1.38)	(-1.72)
2	0.0135*	0.0047	0.0022	0.0157*	0.0459	0.0295
	(1.68)	(0.73)	(0.34)	(1.84)	(1.31)	(1.38)
3	0.0137*	0.0053	0.0029	0.0189*	0.0074	0.0066
	(1.76)	(0.89)	(0.52)	(1.90)	(1.06)	(0.93)
4	0.0104	0.0016	-0.0013	0.0202**	0.0089	0.0059
	(1.28)	(0.26)	(-0.22)	(2.21)	(1.14)	(0.83)
5	0.0161	0.0078	0.0068	0.0073	0.0105	0.0095
	(1.41)	(0.76)	(0.75)	(0.99)	(1.56)	(1.45)
6	0.0108*	0.0039	0.0040	0.0565	-0.0013	-0.0034
	(1.72)	(0.79)	(0.81)	(1.54)	(-0.24)	(-0.67)
7	0.0164*	0.0064	0.0033	0.0028	-0.0061	-0.0091*
	(1.93)	(1.08)	(0.61)	(0.38)	(-1.14)	(-1.72)
8	0.0112	0.0032	0.0012	0.0160**	0.0072	0.0048
	(1.53)	(0.57)	(0.20)	(2.12)	(1.30)	(0.84)
9	0.0063	-0.0017	-0.0034	0.0069	-0.0010	-0.0052
	(0.88)	(-0.30)	(-0.62)	(1.02)	(-0.20)	(-1.19)
Winner	0.0185**	0.0079	0.0044	0.0137*	0.0045	-0.0006
	(2.21)	(1.44)	(0.86)	(1.71)	(0.82)	(-0.13)
Winner-Loser	0.0024	0.0022	0.0008	0.0126**	0.0131**	0.0100**
	(0.44)	(0.39)	(0.14)	(2.19)	(2.36)	(2.02)
Standard deviation	0.0792			0.0796		
Sharpe Ratio	0.030			0.158		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Russian market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.15: Residual Volatility and Total Volatility Performance in Russia

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0184***	0.0009	-0.0006	0.0171***	0.0061	0.0061
	(2.77)	(0.35)	(-0.25)	(3.11)	(1.58)	(1.62)
2	0.0193**	0.0024	0.0034	0.0193**	0.0051	0.0047
	(2.56)	(0.60)	(0.76)	(2.55)	(0.88)	(0.80)
3	0.0162**	0.0016	0.0003	0.0185**	0.0029	0.0017
	(2.57)	(0.46)	(0.10)	(2.47)	(0.58)	(0.35)
4	0.0273***	0.0107*	0.0078	0.0175**	0.0036	0.0031
	(3.31)	(1.92)	(1.56)	(2.40)	(0.68)	(0.61)
5	0.0275***	0.0115**	0.0099*	0.0103	-0.0008	-0.0025
	(3.52)	(2.32)	(1.96)	(1.23)	(-0.11)	(-0.36)
6	0.0062	-0.0067	-0.0081*	0.0235**	0.0050	0.0016
	(0.88)	(-1.35)	(-1.73)	(2.22)	(0.69)	(0.23)
7	0.0175**	0.0018	0.0001	0.0225**	0.0056	0.0049
	(2.09)	(0.30)	(0.02)	(2.53)	(0.89)	(0.73)
8	0.0225**	0.0088	0.0081	0.0185	0.0018	-0.0022
	(2.47)	(1.30)	(1.18)	(1.43)	(0.22)	(-0.27)
9	0.0266**	0.0091	0.0080	0.0209	0.0061	0.0055
	(2.02)	(1.13)	(0.95)	(1.60)	(0.60)	(0.55)
10	0.0177	-0.0003	-0.0025	0.0050	-0.0055	-0.0031
	(1.41)	(-0.04)	(-0.28)	(0.54)	(-0.70)	(-0.35)
D1-D10	0.0007	0.0012	0.0019	0.0079	0.0094	0.0080
	(0.06)	(0.13)	(0.20)	(0.78)	(0.97)	(0.79)
Standard deviation	0.1526			0.1217		
Sharpe Ratio	0.0047			0.0645		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Russian market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.16:(Residual) Momentum Strategies Performance in Brazil

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0193***	0.0056*	0.0033	0.0152**	0.0018	-0.0006
	(3.07)	(1.84)	(1.21)	(2.32)	(0.49)	(-0.18)
2	0.0192***	0.0056*	0.0039	0.0105*	0.0132*	0.0091
	(3.06)	(1.86)	(1.29)	(1.80)	(1.76)	(1.44)
3	0.0181***	0.0046	0.0021	0.0122**	-0.0002	-0.0025
	(2.93)	(1.56)	(0.81)	(2.15)	(-0.05)	(-0.71)
4	0.0192***	0.0072*	0.0046	0.0242***	0.0016	-0.0012
	(3.07)	(1.83)	(1.23)	(4.05)	(0.42)	(-0.38)
5	0.0116**	-0.0000	-0.0014	0.0267***	0.0130***	0.0108***
	(2.02)	(-0.01)	(-0.46)	(4.60)	(3.29)	(2.76)
6	0.0160**	0.0044	0.0014	0.0264***	0.0153***	0.0125***
	(2.49)	(1.04)	(0.36)	(2.70)	(3.94)	(3.53)
7	0.0201***	0.0076**	0.0056*	0.0164***	0.0066	0.0039
	(3.31)	(2.14)	(1.68)	(2.75)	(1.42)	(0.87)
8	0.0207***	0.0090***	0.0063**	0.0167***	0.0055	0.0028
	(3.65)	(2.84)	(2.23)	(2.97)	(1.60)	(0.94)
9	0.0223***	0.0093***	0.0070***	0.0162***	0.0050	0.0020
	(3.70)	(3.16)	(2.68)	(2.90)	(1.51)	(0.70)
Winner	0.0235***	0.0102***	0.0081***	0.0247***	0.0120***	0.0107***
	(3.80)	(3.47)	(3.03)	(4.23)	(4.51)	(4.28)
Winner-Loser	0.0042	0.0046	0.0048	0.0095**	0.0102**	0.0113***
	(1.13)	(1.24)	(1.32)	(2.13)	(2.33)	(2.62)
Standard deviation	0.0563			0.0672		
Sharpe Ratio	0.075			0.141		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Brazil market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.17: Residual Volatility and Total Volatility Performance in Brazil

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0176***	0.0030	0.0016	0.0162***	0.0039	0.0032
	(3.34)	(1.53)	(0.86)	(2.65)	(0.96)	(0.77)
2	0.0147***	-0.0003	-0.0014	0.0196***	0.0063*	0.0054
	(2.73)	(-0.12)	(-0.75)	(3.53)	(1.87)	(1.63)
3	0.0226***	0.0069***	0.0057**	0.0192***	0.0029	0.0012
	(3.87)	(2.76)	(2.42)	(3.00)	(0.90)	(0.40)
4	0.0234***	0.0067***	0.0048**	0.0200***	0.0017	-0.0000
	(3.84)	(2.75)	(2.23)	(2.80)	(0.46)	(-0.00)
5	0.0217***	0.0063**	0.0043*	0.0223***	0.0035	0.0009
	(3.78)	(2.31)	(1.71)	(3.00)	(0.87)	(0.23)
6	0.0291***	0.0127***	0.0099***	0.0228***	0.0055	0.0029
	(4.45)	(3.56)	(3.04)	(3.10)	(1.21)	(0.65)
7	0.0235***	0.0092**	0.0066**	0.0254***	0.0086	0.0056
	(3.94)	(2.59)	(2.04)	(3.19)	(1.58)	(1.09)
8	0.0312***	0.0149***	0.0131***	0.0192**	-0.0007	-0.0045
	(4.43)	(3.12)	(2.96)	(2.21)	(-0.12)	(-0.89)
9	0.0412***	0.0243***	0.0222***	0.0218**	0.0020	0.0011
	(4.67)	(3.43)	(3.28)	(2.25)	(0.29)	(0.16)
10	0.0452***	0.0303***	0.0281***	0.0321***	0.0235***	0.0222***
	(4.71)	(3.28)	(3.09)	(3.84)	(2.82)	(2.66)
D1-D10	-0.0276***	-0.0273***	-0.0265***	-0.0400***	-0.0358**	-0.0315**
	(-3.28)	(-2.89)	(-2.80)	(-2.76)	(-2.30)	(-2.05)
Standard deviation	0.1283			0.1608		
Sharpe Ratio	-0.2153			-0.2490		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Brazil market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.18:(Residual) Momentum Strategies Performance in Mexico

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0169***	0.0071***	0.0056**	0.0158***	0.0049	0.0029
	(3.79)	(2.66)	(2.29)	(2.82)	(1.23)	(0.79)
2	0.0096*	-0.0011	-0.0030	0.0091	0.0059	0.0043
	(1.96)	(-0.35)	(-1.12)	(1.64)	(1.42)	(1.05)
3	0.0128***	0.0030	0.0009	0.0136***	-0.0009	-0.0027
	(2.81)	(0.94)	(0.35)	(2.74)	(-0.23)	(-0.72)
4	0.0163***	0.0045	0.0029	0.0158***	0.0051	0.0039
	(2.66)	(1.25)	(0.83)	(2.77)	(1.24)	(0.91)
5	0.0159***	0.0051	0.0036	0.0138***	0.0061	0.0052
	(3.07)	(1.53)	(1.13)	(3.39)	(1.38)	(1.13)
6	0.0133**	0.0028	0.0008	0.0164***	0.0059*	0.0046
	(2.06)	(0.54)	(0.18)	(2.95)	(1.86)	(1.45)
7	0.0169***	0.0068**	0.0056*	0.0170***	0.0083**	0.0070
	(3.54)	(2.20)	(1.73)	(3.43)	(2.00)	(1.62)
8	0.0183***	0.0076***	0.0068***	0.0180***	0.0082*	0.0062
	(3.97)	(3.09)	(3.01)	(2.71)	(1.93)	(1.45)
9	0.0118**	0.0001	-0.0010	0.0150***	0.0056**	0.0038**
	(2.33)	(0.03)	(-0.37)	(3.60)	(2.41)	(2.00)
Winner	0.0195***	0.0092**	0.0075**	0.0117***	0.0021	0.0006
	(3.77)	(2.54)	(2.39)	(2.74)	(0.88)	(0.30)
Winner-Loser	0.0026	0.0021	0.0019	-0.0040	-0.0027	-0.0017
	(0.62)	(0.51)	(0.47)	(-0.87)	(-0.59)	(-0.37)
Standard deviation	0.0626			0.0684		
Sharpe Ratio	0.04			-0.06		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Mexico market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.19: Residual Volatility and Total Volatility Performance in Mexico

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0101***	0.0007	0.0003	0.0128***	0.0038	0.0019
	(2.88)	(0.33)	(0.13)	(3.60)	(1.64)	(0.92)
2	0.0135***	0.0023	0.0005	0.0121***	0.0009	-0.0008
	(3.37)	(1.02)	(0.25)	(2.90)	(0.38)	(-0.35)
3	0.0180***	0.0051***	0.0032*	0.0183***	0.0051*	0.0045*
	(4.12)	(2.60)	(1.81)	(3.83)	(1.94)	(1.71)
4	0.0151***	0.0025	0.0003	0.0155***	0.0018	-0.0001
	(3.36)	(0.96)	(0.13)	(3.06)	(0.57)	(-0.03)
5	0.0162***	0.0024	0.0008	0.0150***	0.0017	0.0001
	(3.28)	(0.80)	(0.29)	(3.06)	(0.64)	(0.04)
6	0.0144***	0.0002	-0.0014	0.0135**	-0.0023	-0.0032
	(2.70)	(0.05)	(-0.53)	(2.23)	(-0.57)	(-0.80)
7	0.0259***	0.0129***	0.0102***	0.0179***	0.0027	0.0005
	(4.78)	(3.85)	(3.21)	(3.15)	(0.77)	(0.17)
8	0.0178***	0.0031	-0.0001	0.0286***	0.0127***	0.0105**
	(3.10)	(0.81)	(-0.03)	(4.07)	(2.67)	(2.44)
9	0.0263***	0.0132***	0.0104**	0.0233***	0.0075	0.0065
	(4.44)	(2.96)	(2.47)	(3.16)	(1.31)	(1.11)
10	0.0338***	0.0205**	0.0146**	0.0260***	0.0132	0.0091
	(3.32)	(2.42)	(2.22)	(2.80)	(1.58)	(1.17)
D1-D10	-0.0237**	-0.0198**	-0.0143**	-0.0179*	-0.0128	-0.0101
	(-2.45)	(-2.26)	(-2.05)	(-1.83)	(-1.37)	(-1.13)
Standard deviation	0.1452			0.1364		
Sharpe Ratio	-0.1635			-0.1311		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Mexico market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.20:(Residual) Momentum Strategies Performance in Indonesia

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0211***	0.0092***	0.0053	0.0289***	0.0158***	0.0124***
	(3.94)	(2.74)	(1.65)	(4.50)	(4.01)	(3.06)
2	0.0240***	0.0122***	0.0085***	0.0313***	0.0186***	0.0165***
	(4.39)	(3.76)	(2.83)	(3.31)	(3.60)	(3.38)
3	0.0205***	0.0090***	0.0058**	0.0482***	0.0179***	0.0116**
	(3.92)	(3.01)	(2.09)	(4.62)	(2.89)	(2.49)
4	0.0277***	0.0152***	0.0120***	0.0358***	0.0380***	0.0306***
	(4.85)	(4.56)	(3.70)	(4.37)	(3.94)	(3.67)
5	0.0250***	0.0130***	0.0115***	0.0296***	0.0260***	0.0229***
	(4.24)	(3.37)	(2.64)	(5.48)	(3.41)	(3.54)
6	0.0284***	0.0175***	0.0139***	0.0307***	0.0180***	0.0139***
	(4.80)	(4.02)	(3.56)	(4.36)	(5.49)	(4.57)
7	0.0221***	0.0095***	0.0056*	0.0295***	0.0186***	0.0145***
	(3.86)	(2.94)	(1.84)	(5.38)	(4.96)	(4.28)
8	0.0272***	0.0149***	0.0115***	0.0295***	0.0164***	0.0124***
	(4.94)	(4.61)	(3.55)	(4.61)	(4.42)	(3.59)
9	0.0322***	0.0204***	0.0153***	0.0244***	0.0146***	0.0111***
	(5.63)	(5.81)	(4.54)	(5.25)	(5.38)	(4.36)
Winner	0.0391***	0.0270***	0.0221***	0.0200***	0.0088***	0.0049***
	(5.63)	(4.84)	(3.49)	(4.28)	(3.94)	(2.78)
Winner-Loser	0.0179***	0.0178***	0.0168**	-0.0089*	-0.0069	-0.0075*
	(2.93)	(2.71)	(2.19)	(-1.88)	(-1.59)	(-1.66)
Standard deviation	0.0920			0.0710		
Sharpe Ratio	0.19			-0.13		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Indonesia market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.21: Residual Volatility and Total Volatility Performance in Indonesia

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0160***	0.0035*	0.0031	0.0144***	0.0051	0.0021
	(3.68)	(1.79)	(1.58)	(3.29)	(1.55)	(0.73)
2	0.0188***	0.0059***	0.0041*	0.0214***	0.0080**	0.0063*
	(4.15)	(2.75)	(1.97)	(4.02)	(2.15)	(1.89)
3	0.0238***	0.0102***	0.0076***	0.0162***	0.0023	-0.0000
	(4.96)	(4.48)	(3.65)	(3.13)	(0.76)	(-0.01)
4	0.0204***	0.0058**	0.0032	0.0279***	0.0111**	0.0095
	(3.99)	(2.40)	(1.35)	(3.96)	(2.26)	(1.65)
5	0.0264***	0.0107***	0.0068***	0.0223***	0.0052	0.0035
	(4.71)	(3.80)	(2.66)	(3.53)	(1.54)	(0.97)
6	0.0307***	0.0155***	0.0104***	0.0249***	0.0084**	0.0054
	(5.21)	(4.44)	(3.32)	(3.81)	(2.07)	(1.36)
7	0.0391***	0.0247***	0.0193***	0.0228***	0.0061	0.0026
	(6.53)	(6.03)	(4.97)	(3.16)	(1.25)	(0.54)
8	0.0398***	0.0264***	0.0216***	0.0300***	0.0132**	0.0066
	(6.31)	(5.49)	(4.52)	(3.84)	(2.22)	(1.13)
9	0.0398***	0.0273***	0.0209***	0.0352***	0.0190***	0.0134*
	(6.53)	(5.78)	(4.82)	(4.18)	(2.67)	(1.82)
10	0.0539***	0.0388***	0.0302***	0.0477***	0.0309***	0.0183**
	(7.26)	(6.95)	(5.82)	(4.20)	(3.39)	(2.05)
D1-D10	-0.0378***	-0.0353***	-0.0271***	-0.0347***	-0.0266***	-0.0172*
	(-6.08)	(-6.07)	(-4.84)	(-3.04)	(-2.64)	(-1.72)
Standard deviation	0.0957			0.1722		
Sharpe Ratio	-0.3951			-0.2016		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Indonesia market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.22:(Residual) Momentum Strategies Performance in Turkey

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0267***	0.0166***	0.0089***	0.0201***	0.0101**	0.0025
	(3.55)	(4.11)	(2.79)	(2.70)	(2.53)	(0.74)
2	0.0230***	0.0128***	0.0064**	0.0223***	0.0139**	0.0037
	(3.19)	(3.80)	(2.21)	(2.87)	(2.44)	(0.98)
3	0.0193***	0.0095***	0.0024	0.0279***	0.0125***	0.0055
	(2.71)	(2.73)	(0.83)	(3.49)	(2.79)	(1.48)
4	0.0240***	0.0143***	0.0064**	0.0300***	0.0172***	0.0081**
	(3.38)	(3.96)	(2.28)	(3.85)	(4.09)	(2.51)
5	0.0220***	0.0119***	0.0039	0.0339***	0.0192***	0.0120***
	(3.01)	(3.33)	(1.45)	(4.49)	(5.07)	(3.71)
6	0.0277***	0.0169***	0.0092***	0.0238***	0.0236***	0.0155***
	(3.53)	(4.39)	(2.93)	(2.81)	(6.07)	(5.48)
7	0.0272***	0.0167***	0.0081***	0.0356***	0.0253***	0.0175***
	(3.61)	(4.73)	(2.78)	(4.79)	(6.90)	(6.13)
8	0.0331***	0.0233***	0.0147***	0.0323***	0.0226***	0.0155***
	(4.46)	(5.71)	(4.88)	(4.48)	(6.06)	(4.91)
9	0.0302***	0.0203***	0.0130***	0.0325***	0.0231***	0.0153***
	(3.90)	(4.57)	(3.68)	(4.65)	(6.24)	(4.98)
Winner	0.0348***	0.0248***	0.0167***	0.0221***	0.0130***	0.0057**
	(4.46)	(5.58)	(4.55)	(3.40)	(4.25)	(2.38)
Winner-Loser	0.0082*	0.0082*	0.0078*	0.0020	0.0029	0.0032
	(1.72)	(1.77)	(1.66)	(0.54)	(0.79)	(0.90)
Standard deviation	0.0713			0.0550		
Sharpe Ratio	0.012			0.04		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Turkish market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.23: Residual Volatility and Total Volatility Performance in Turkey

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0194***	0.0071***	0.0015	0.0225***	0.0116***	0.0053
	(2.90)	(2.89)	(0.73)	(3.24)	(2.71)	(1.30)
2	0.0244***	0.0115***	0.0053**	0.0317***	0.0198***	0.0126***
	(3.49)	(4.42)	(2.59)	(3.96)	(3.87)	(2.60)
3	0.0214***	0.0091***	0.0028	0.0305***	0.0179***	0.0098**
	(3.17)	(3.31)	(1.33)	(3.63)	(3.34)	(2.26)
4	0.0313***	0.0196***	0.0121***	0.0286***	0.0167***	0.0076*
	(4.10)	(4.03)	(3.92)	(3.63)	(3.26)	(1.68)
5	0.0297***	0.0175***	0.0106***	0.0227***	0.0110**	0.0034
	(4.20)	(5.07)	(3.74)	(3.07)	(2.52)	(0.90)
6	0.0288***	0.0161***	0.0074***	0.0409***	0.0283***	0.0208***
	(3.87)	(4.32)	(2.83)	(4.09)	(3.90)	(2.96)
7	0.0306***	0.0186***	0.0117***	0.0329***	0.0208***	0.0095
	(4.40)	(5.40)	(4.22)	(3.29)	(2.71)	(1.59)
8	0.0352***	0.0228***	0.0144***	0.0249***	0.0142**	0.0021
	(4.65)	(5.44)	(4.30)	(2.86)	(2.14)	(0.38)
9	0.0381***	0.0256***	0.0170***	0.0330***	0.0208***	0.0113*
	(4.67)	(5.16)	(3.90)	(3.26)	(2.71)	(1.67)
10	0.0362***	0.0246***	0.0171***	0.0292***	0.0181**	0.0073
	(4.57)	(4.75)	(3.71)	(3.08)	(2.40)	(1.12)
D1-D10	-0.0168***	-0.0176***	-0.0156***	-0.0122	-0.0110	-0.0063
	(-3.16)	(-3.41)	(-3.12)	(-1.54)	(-1.41)	(-0.88)
Standard deviation	0.0818			0.1156		
Sharpe Ratio	-0.2058			-0.1053		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Turkish market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.24(Residual) Momentum Strategies Performance in Thailand

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0126***	0.0045**	0.0027	0.0113***	0.0030	0.0014
	(3.06)	(2.06)	(1.28)	(2.70)	(1.39)	(0.64)
2	0.0116***	0.0036	0.0010	0.0143***	0.0067	0.0040
	(2.81)	(1.52)	(0.46)	(3.79)	(1.51)	(0.99)
3	0.0157***	0.0081***	0.0059***	0.0154***	0.0071***	0.0054***
	(4.06)	(3.90)	(3.02)	(3.94)	(3.28)	(2.77)
4	0.0058*	0.0006	-0.0025	0.0168***	0.0079***	0.0055***
	(1.85)	(0.30)	(-1.26)	(4.40)	(3.65)	(2.91)
5	-0.0022	-0.0035*	-0.0045**	0.0227***	0.0096***	0.0069***
	(-1.39)	(-1.93)	(-2.43)	(4.88)	(4.41)	(3.49)
6	0.0050**	0.0035**	0.0042***	0.0153**	0.0152***	0.0125***
	(2.52)	(2.29)	(2.62)	(2.55)	(4.69)	(3.81)
7	0.0094**	0.0035	0.0015	0.0172***	0.0095***	0.0075***
	(2.34)	(1.07)	(0.41)	(4.37)	(4.85)	(3.75)
8	0.0163***	0.0091***	0.0068**	0.0170***	0.0101***	0.0076***
	(3.67)	(2.78)	(2.06)	(4.85)	(5.54)	(4.54)
9	0.0205***	0.0126***	0.0091***	0.0195***	0.0130***	0.0096***
	(4.79)	(4.87)	(4.46)	(5.57)	(6.06)	(6.79)
Winner	0.0169***	0.0079***	0.0050**	0.0158***	0.0083***	0.0047***
	(3.76)	(3.47)	(2.41)	(4.20)	(4.31)	(3.27)
Winner-Loser	0.0043	0.0033	0.0023	0.0045*	0.0053**	0.0033
	(1.63)	(1.26)	(0.82)	(1.70)	(2.14)	(1.29)
Standard deviation	0.0399			0.0394		
Sharpe Ratio	0.108			0.1142		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Thailand market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.25: Residual Volatility and Total Volatility Performance in Thailand

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0123***	0.0050***	0.0033**	0.0112***	0.0057***	0.0041***
	(4.12)	(3.04)	(2.31)	(4.70)	(4.03)	(3.33)
2	0.0135***	0.0047**	0.0026	0.0124***	0.0055***	0.0028*
	(3.59)	(2.32)	(1.37)	(4.08)	(2.96)	(1.74)
3	0.0144***	0.0060***	0.0042**	0.0129***	0.0045**	0.0020
	(4.11)	(3.15)	(2.07)	(3.66)	(2.38)	(1.14)
4	0.0143***	0.0046**	0.0024	0.0135***	0.0042**	0.0029
	(3.60)	(2.19)	(1.23)	(3.63)	(2.19)	(1.54)
5	0.0157***	0.0052**	0.0019	0.0177***	0.0062***	0.0056**
	(3.53)	(2.06)	(0.78)	(3.90)	(2.66)	(2.04)
6	0.0204***	0.0097***	0.0080***	0.0212***	0.0098***	0.0074**
	(4.38)	(3.36)	(2.67)	(3.99)	(2.98)	(2.26)
7	0.0183***	0.0077**	0.0036	0.0211***	0.0086***	0.0050*
	(3.84)	(2.57)	(1.46)	(3.82)	(2.66)	(1.76)
8	0.0241***	0.0124***	0.0059*	0.0245***	0.0090**	0.0044
	(4.34)	(3.50)	(1.84)	(3.52)	(2.15)	(1.11)
9	0.0253***	0.0121***	0.0071**	0.0212***	0.0066	0.0000
	(4.12)	(3.05)	(2.06)	(2.99)	(1.41)	(0.01)
10	0.0298***	0.0182***	0.0087*	0.0371***	0.0254***	0.0116*
	(3.96)	(2.98)	(1.65)	(3.86)	(3.16)	(1.73)
D1-D10	-0.0175***	-0.0132**	-0.0054	-0.0259***	-0.0197**	-0.0076
	(-2.66)	(-2.12)	(-0.98)	(-2.94)	(-2.48)	(-1.11)
Standard deviation	0.1012			0.1357		
Sharpe Ratio	-0.1731			-0.1912		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Thailand market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.26(Residual) Momentum Strategies Performance in Israel

Decile	Residual Momentum			Conventional Momentum		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
Loser	0.0136***	0.0056**	0.0013	0.0095*	0.0010	-0.0036
	(2.79)	(1.98)	(0.55)	(1.76)	(0.30)	(-1.35)
2	0.0146***	0.0070**	0.0029	0.0163***	0.0029	-0.0013
	(3.03)	(2.30)	(1.17)	(2.66)	(0.92)	(-0.46)
3	0.0168***	0.0086**	0.0048	0.0140***	0.0082*	0.0038
	(2.93)	(2.52)	(1.49)	(2.89)	(1.80)	(0.82)
4	0.0132***	0.0060**	0.0023	0.0201***	0.0072**	0.0034
	(2.89)	(2.25)	(0.93)	(4.09)	(1.98)	(1.02)
5	0.0089**	0.0015	-0.0013	0.0170***	0.0136***	0.0094***
	(2.00)	(0.58)	(-0.57)	(3.46)	(3.85)	(2.96)
6	0.0116**	0.0038	0.0001	0.0095**	0.0096***	0.0047*
	(2.45)	(1.45)	(0.05)	(2.09)	(3.05)	(1.71)
7	0.0185***	0.0114***	0.0079***	0.0176***	0.0110***	0.0063**
	(4.30)	(4.72)	(3.89)	(3.65)	(3.41)	(2.48)
8	0.0177***	0.0101***	0.0062**	0.0179***	0.0117***	0.0081***
	(3.72)	(3.59)	(2.50)	(4.23)	(4.07)	(3.05)
9	0.0153***	0.0078***	0.0038*	0.0175***	0.0113***	0.0075***
	(3.30)	(2.93)	(1.72)	(4.49)	(4.75)	(4.08)
Winner	0.0159***	0.0080***	0.0045**	0.0177***	0.0108***	0.0077***
	(3.37)	(3.20)	(2.18)	(4.35)	(5.18)	(4.65)
Winner-Loser	0.0023	0.0023	0.0032	0.0082**	0.0098***	0.0113***
	(0.79)	(0.81)	(1.05)	(2.24)	(2.79)	(3.36)
Standard deviation	0.0438			0.0550		
Sharpe Ratio	0.053			0.149		

This table displays the performance of equally-weighted decile portfolios of the Residual momentum and Conventional Momentum for the Israel market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.

Table A.27: Residual Volatility and Total Volatility Performance in Israel

Decile	Residual Volatility			Total Volatility		
	Return-Rf	CAPM	FF3	Return-Rf	CAPM	FF3
1	0.0160***	0.0068***	0.0044***	0.0134***	0.0056***	0.0034**
	(4.02)	(3.77)	(2.74)	(3.79)	(2.92)	(2.06)
2	0.0150***	0.0058***	0.0021	0.0160***	0.0077***	0.0046**
	(3.60)	(2.65)	(1.27)	(4.09)	(3.41)	(2.43)
3	0.0163***	0.0068***	0.0035*	0.0176***	0.0080***	0.0046*
	(3.76)	(2.99)	(1.74)	(3.88)	(3.04)	(1.94)
4	0.0184***	0.0086***	0.0049**	0.0176***	0.0079***	0.0049**
	(4.10)	(3.63)	(2.45)	(3.78)	(3.14)	(2.03)
5	0.0154***	0.0060***	0.0028	0.0154***	0.0055*	0.0017
	(3.53)	(2.61)	(1.38)	(3.24)	(1.91)	(0.71)
6	0.0175***	0.0078***	0.0037*	0.0208***	0.0109***	0.0062**
	(3.85)	(3.00)	(1.72)	(4.00)	(3.10)	(2.10)
7	0.0169***	0.0072***	0.0035	0.0174***	0.0080**	0.0035
	(3.76)	(2.90)	(1.57)	(3.52)	(2.31)	(1.17)
8	0.0210***	0.0111***	0.0062**	0.0238***	0.0119***	0.0079**
	(4.17)	(3.55)	(2.35)	(3.96)	(3.17)	(2.27)
9	0.0233***	0.0122***	0.0090**	0.0161***	0.0054	0.0017
	(3.86)	(3.26)	(2.45)	(2.70)	(1.27)	(0.41)
10	0.0293***	0.0192***	0.0155***	0.0271***	0.0155***	0.0116**
	(4.37)	(3.67)	(2.92)	(3.67)	(2.75)	(2.01)
D1-D10	-0.0133**	-0.0124**	-0.0110**	-0.0137**	-0.0098*	-0.0081
	(-2.44)	(-2.37)	(-2.03)	(-2.21)	(-1.67)	(-1.34)
Standard deviation	0.0843			0.0959		
Sharpe Ratio	-0.1579			-0.1433		

This table displays the performance of equally-weighted decile portfolios of the Residual and Total Volatility for the Israel market for the period January 2004 through to December 2022.Newey-west robust t-statistics are given in parentheses. *, **, *** reflect statistical significance at 10%, 5% and 1% levels, respectively.