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Momentum and Low Volatility During the History

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Abstract

The ever-presence of stock market anomalies poses a serious challenge to the market efficiency theory as well as to the researchers who seek for an explanation for these anomalies. However, most of these anomalies do not work consistently in different periods of time or markets. Low volatility and Momentum are two of the anomalies which have been confirmed to work in an extensive range of settings. This paper takes another look at these two anomalies during the entire history of the New York Stock Exchange (NYSE) and London Stock Exchange (LSE), two of the biggest and most historically important exchanges in the world. Surprisingly, I do not find evidence of Low Volatility and Momentum anomaly in these markets. Instead, reverse effects of these anomalies are found in the NYSE dataset. The lack of consistency in performance of these anomalies between different markets and periods of time may imply that these investing tactics are not entirely riskless.

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1. Introduction

Ever since the discovery of the CAPM model which shows a strong correlation between market returns and stock returns, researchers and investors have been trying to develop strategies to beat the market. As a consequence, a huge number of anomalies are discovered. After computers were introduced to mainstream uses which makes data processing and analyzing much faster and easier, the rate of which new anomalies are discovered has skyrocketed. New anomalies are now discovered every day and everywhere. However, to be considered a true anomaly, a strategy not only needs to consistently beat the market after adjusting for all risks but also needs to present investors a possibility to profit from such strategies. Which, along with the fact that many anomalies become less pronounced after their discovery, raises the question that whether these anomalies are really anomalous or just results of random events or data mining, and one way to mitigate this concern is to observe these anomalies under different times and situations.

Low volatility and momentum are among a few anomalies which manage to consistently beat the market after extensive examination in different sample periods and markets. So far, most research on the matter focuses only on the US market and from 1926, which is also the furthest point of time that the data is available from CSPR. Some papers manage to push the matter further, notably Geczy and Samolov (2016), using a data set of US stocks which spans back to 1800, find that momentum has always been present during the last 200 years. In the end, a complete picture of how low volatility and momentum strategies perform during the history of stock markets is still up to be explored.

With the data set provided by GFD, CRSP, and Datastream, I manage to put together a data set of stock returns from two of the biggest and oldest stock exchanges in the world, NYSE and LSE. The sample spans back to 1602, the year of establishment of LSE, which allows for a more extensive examination of the existence and performance of low volatility and momentum during the history of these markets. The anomalies can now be investigated thoroughly both in isolated markets and in a combined data set.

My research makes the following contributions to the existing research: Firstly, I put together a complete dataset of monthly stock price and return from NYSE and LSE, two of the biggest stock exchanges in the world. In my research, modern data provided by CRPS and DataStream is combined with older data from GFD to create a dataset spanning from 1602 to 2017, which can also be used in other research in the field. The second contribution of this research is extending the momentum and low volatility testing to a new dataset with a much wider scope. Evidently, momentum and low volatility have little presence in the global data set. Further research into regional markets reveals that momentum and low volatility work very differently and unexpectedly for each market which cancels out their presences in the global market. Lastly, my research provides further evidence that the results of anomaly studies can differ greatly depending on the choice of data samples and data cleaning techniques as well as research methodology.

The paper continues as follows: the next section provides the theoretical background of low volatility and momentum anomaly along with residual momentum, which is a newly discovered, improved version of momentum strategy. Section 3: Data and methodology will explain how data is collected and processed along with the methodology used in this research. Section 4 will then present the empirical findings while the last section, Section 5 and 6, will tie up the research with discussions and conclusions.

2. Literature overview

During the years, many relatively simple investing strategies have challenged the efficient markets theory by statistically significantly outperforming market portfolio in terms of return. Momentum is among the well-known examples, for which excess premiums have been documented in many different stock markets. Market efficiency is also questioned, however, when some simple investment strategies can generate a return similar to that of the market, but at a lower level of risk systematically, in which case, low volatility is one of the most notable examples.

2.1 Low volatility

Clarke, Thorley and de Silva (2006) discover interesting characteristics of minimum variance portfolios in their empirical analysis. Specifically, the minimum variance portfolios, which are formed from 1000 US stocks during the 1968-2005 period, reduce their volatilities by around 25% while achieving similar returns to the market portfolio. Ang, Xing, Hodrick & Zhang (2006) add to the robustness of low volatility literature with their study of US stocks during 1963-2000 period. When focusing on very short-term volatility returns of stocks (1 month), these authors find out that highly volatile stocks yield abnormally low returns, not enough to compensate for the high level of risk taking.

Improve upon the previous studies, Blitz and van Vliet (2007) develop an alternative method to achieve similar risk and return characteristics of the minimum variance portfolio. They sort stocks into decile portfolios based on the historical volatility of these stocks' returns. Different from Ang, Xing, Hodrick & Zhang (2006), this study focuses on long term volatility of 36 months, which implies a much lower portfolio turnover, thus reduces transaction costs. The strategy is also able to produce higher Sharpe ratio in portfolios with stocks that have lower historical alphas along with a positive, statistically alpha after controlling for risk factors. As a conclusion, the research finds that not only highly volatile stocks underperform but also low-risk stocks do particularly well in the tradeoff between risk and return.

However, low (high) risk stocks inherently come with low (high) historical market beta, a strategy which ranks stocks based on their volatility can be similar to ranking stocks based on their market beta. This comes from the fact the correlation between a stock return and market return is a part of the calculation for CAPM beta. Indeed, Blitz and van Vliet (2007) also observe high (low) betas in portfolios with high (low) volatility of historical return. This finding is supported by earlier research, for example, Black, Jensen, and Scholes (1972) report a positive alpha from stock with low beta. However, while Fama and French (1992) show that market beta did not predict returns in the 1962-1990 period, Blitz and van Vliet (2007) report superior performance of the strategy which ranks stocks based on their historical risk profiles.

Currently, there are a few possible explanations for the low volatility anomaly. Firstly, leverage may not be available to all investors at all time as pointed out by Black (1972), Blitz and van Vliet (2007) and others. As a result, mispricing presented by low-risk stocks cannot be easily arbitraged away. Secondly, benchmark driven investing put a pressure on fund's managers to beat the market, which makes highly volatile stocks become more attractive and overpriced. The third possible explanation is biased among private investors. Shefrin and Statman (2000) argue that investors tend to have different layers in their investment, in which the high-risk layer acts more like a lottery ticket rather than a well-managed risk-averse portfolio. The risk-seeking behavior presented from this layer may cause overpricing in high-risk stock while leaves the low-risk ones underpriced.

2.2 Momentum and residual momentum

Contrary to low volatility, which is a fairly newly discovered anomaly, momentum has been investigated extensively, many strategies are also found to improve the performance of the momentum strategy.

In one of the earliest researches on the matter, Levy (1967) claim that stocks that are traded substantially higher than their 27-week moving average achieve a higher return. The claim was soon challenged when Jensen and Bennington (1970) show that buy-and-hold strategy can achieve similar results which suggest Levy's findings could be a result of data mining. Fast forward to 1989, Grinblatt and Titman (1989) find that mutual fund managers tend to put winner stocks in their portfolios – a buying decision that seems similar to momentum strategy. Along with momentum, reversal effect was also quickly discovered, Lehmann (1990) discovers a strategy which exploits short run reversal effect and shows that momentum and reversal are interesting anomalies.

Jegadeesh and Titman (1993) develop a trading strategy which can be considered a foundation for many later research on the anomaly. The strategy relies on buying winner and selling loser stocks with various formation and holding periods. A vast number of subsequent researches confirm their findings with data from markets in different regions; Rouwenhorst (1998). Asness et al. (2008)

manage to expand the momentum literature to other classes of assets including country equity indexes, government bonds, currencies, and commodities. Generally, there is a reversal effect in very short term as the WML (winner minus loser) portfolios underperform in the first months after its formation. WML portfolios then perform well in intermediate-term which is 2 to 12 months before long-term reversal effect starts to appear. Over 36 to 60 months after formation, excess returns from momentum effect will completely disappear. The profits from the momentum strategy are substantial and cannot be explained by transaction costs despite its fairly high re-balancing frequency. Korajczyk and Sadka (2004), with their estimations of visible and invisible transaction costs, estimate that returns from momentum investing only start to disappear after around $5 billion is put into the strategy.

A good variety of explanations has been proposed and explored for the anomaly, which ranges from data issues, such as micro movements from micro stocks and data mining [Lo and MacKinlay (1988), Boudoukh et al. (1994)], to risk-related explanations [Conrad & Kaul (1998), Berk et al. (1999), Shivakumar & Chordia (2002), Bensal et al. (2002)], to irrational aspects of investors' behaviors [Jegadeesh & Titman (1993), DeBondt & Thaler (1985, 1987), Daniel et al. (1998), Grinblatt & Han (2002), Barberis et al. (1998), Hong & Stein (1999), Hong et al. (2000), Swaminathan & Lee (2000), among others].

Overall, the theories that are put forward to explain this anomaly can be put into two classes: those that focus on investor psychological aspects of investors' behaviors while the others focus on the changing nature of real investment opportunities presented to investors at different times; Chabot et al. (2009).

Residual momentum

Since conventional momentum revolves around buying past winners, selling past losers and expects the trend to continue, Blitz et al. (2011) argue that the strategy essentially places a bet on the persistence of common-factor returns, which affect the risk and return characteristics. Consider this example: when the market is going up, a winner portfolio will consist mostly of high-beta stock while low-beta stocks will be in the loser portfolio. As a result, momentum portfolios will resemble characteristics of portfolios formed based on market beta. In general, winner portfolios always consist of stocks with high loading on factors that performs well in the preceding period and vice-versa.

The performance of a strategy based on momentum will be positively affected by these dynamic exposures if the performance of the factors persists, however, there is a risk that these factor returns revert which will negatively affect the performance. Blitz et al. (2011) find out that a substantial portion of the risk of momentum is from the factor exposures. Specifically, they show that Fama and French's 3 factors account for roundly 50% of the risk that conventional momentum strategy presents while only 25% of the profits can be attributed to them.

In order to deal with this concern, Blitz et al. (2011) develop residual momentum as an improvement to conventional momentum. In this strategy, instead of ranking the stocks based on their raw total returns, they rank the stocks based on the residual returns after accounting for other risk factors, hence residual momentum. This strategy shows to be effective in neutralizing the factor exposures of conventional momentum, in their research, the exposures are reduced by three to five times compared to conventional momentum. Compared to conventional momentum, residual momentum has similar returns but only with half of the risk between 1926 and 2009 in the US market.

3. Data and methodology

3.1 Data

Data overview

In the research, I focus only on common equity and exclude Closed-end funds, Real Estate Investment Trusts (REITs), unit trusts, American Depository Receipts (ADRs), and foreign stocks from the analysis. This approach is consistent with most of the stock market anomalies' empirical literature [see, e.g., Jegadeesh and Titman (1993; 2001), Chan, Lakonishok and Jegadeesh (1996), Rouwenhorst (1998), Griffin, Ji & Martin (2003), Grundy and Martin (2003), Schwert (2003)].

Monthly returns of stocks listed on NYSE and LSE since the inception of these stock exchanges are collected from three primary sources: Global Financial Data (GFD) and CRSP for NYSE; and GFD and DataStream for LSE. Specifically, CRPS provides the data for all stocks which have been listed on NYSE since 1925 while DataStream provides the data for LSE since 1965. Earlier data needs to be extracted from GFD, which is a fairly new and less well-known source of financial data. All price data from GFD is dividend-adjusted, the procedure is performed automatically by GFD, therefore, the stock returns consist of both price returns and dividend returns. Overall, the combined data set consists of 4,853,394 observations pre-cleaning and covers 400 years of stock returns, from 1602 to 2017. The choice of these exchange is influenced by the availability of data and the fact that these exchanges are among the biggest and most important stock exchanges in the world. Detailed statistics for the datasets are shown in Table 1 below:

Data source	Period	Avg. Monthly return (%)	Total # of unique securities	Avg. # of securities at a point of time	Total # of Observations
CRSP (NYSE)	1926-2017	0.859	3,940	716	790,030
GFD (NYSE)	1792-2017	1.017	1,653	259	694,427
Merged (NYSE)	1792_2017	0.948	5,593	554	1,484,457
Datastream (LSE)	1966-2017	0.769	6,864	3,605	2,271,440
GFD (LSE)	1602-2014	1.343	4,806	308	1,097,497
Merged (LSE)	1602-2017	1.228	11,670	851	3,368,937
Merged (Global)	1602-2017	1.178	17,263	1,226	4,853,394

Table 1: Descriptive statistics for the Datasets

Compared to Geczy and Samonov (2016), on which I base this research on, my research only focuses on one American exchange which is NYSE instead of the whole market, at the same time, I also cover LSE stocks which is a vastly different market from that of Geczy and Samonov (2016).

Data cleaning procedure

Due to the limitations in data recording techniques in the early days of stock exchanges, human errors are an inevitable part of the process. Therefore, several data cleaning techniques are applied in order to mitigate these concerns.

Firstly, I exclude stocks with prices lower than $5 to avoid the effect of micro movements. For research that involves a very long period of time, dynamic thresholds to identify micro stocks are preferable, however, due to the lack of reliable data on market capitalization of the stocks in various periods of time, this idea is impractical. In the end, the results found in this research is robust at different micro stock thresholds, which are $1, $3 and $5. Stock data from the early days is usually incomplete and has a lot of missing observations, therefore, linearly interpolated values are used to fill in these missing points. However, over-usage of linearly interpolated values will have an impact on stocks' volatility and need to apply with caution. Specifically, stocks with more than 3 consecutive missing points are excluded as there is no effective ways to recover the data. I also exclude stocks with unchanged prices for more than 6 months due to illiquidity concerns.

	Global	LSE	NYSE
1690s	4.6	4.6	
1700s	-14.3	-14.3	
1710s	-2.1	-2.4	
1720s	44.3	44.5	
1730s	-2.1	-2.1	
1740s	-3.5	-3.5	
1750s	-4.6	-4.6	
1760s	-0.2	-0.1	
1770s	-6.8	-6.8	
1780s	0.9	0.9	
1790s	-10.1	-4.9	-173.9
1800s	0.5	2.7	-4.0
1810s	-9.2	-6.5	-21.4
1820s	-4.9	6.2	-14.0
1830s	23.4	46.5	-8.6
1840s	43.5	49.7	0.4
1850s	9.6	17.8	-13.8
1860s	32.9	38.4	8.0
1870s	24.9	26.3	17.9
1880s	15.8	11.2	21.6
1890s	13.7	4.2	22.1
1900s	3.4	-6.1	8.7
1910s	5.7	3.9	6.5
1920s	4.9	-4.6	7.2
1930s	13.8	-0.3	17.8
1940s	7.7	2.6	9.1
1950s	9.0	10.1	8.1
1960s	0.6	-0.7	-0.2
1970s	2.3	4.9	-2.0
1980s	1.6	8.8	-0.4
1990s	2.8	6.9	2.0
2000s	5.8	4.3	6.0
2010s	14.4	12.8	17.1

Table 2: Average equity premium (%) by decade. Equity premia are calculated by subtracting risk free rates for the respected market from its market return.

Disappearing stocks are another problem when dealing with data from the early days. Most of the times, there is no clear indication of what happened to the stocks, whether they were delisted or just the data is missing. For this problem, I allow 12 months buffer after a stock disappears. If the stocks do not reappear after 12 months, I assign -1 to the returns of these stocks. Note that this approach understates the real returns but allows the conservativeness of the research. Assigning -1 to the return of the disappearing stocks also help to mitigate the survivorship bias. Fortunately, even though the approach understates the returns, most of the times, these stocks' prices slowly decline to zero before disappearing completely which is a good sign of a company going of business. Finally, periods, when there are fewer than 30 stocks available, are all dropped from the sample, this minimum number of stocks allows the formation of decile portfolios which is fundamental to the strategies.

Overall, the ways I deal with the data errors in this research tend to understate the returns of individual stocks in order to maintain a conservative perspective on the performances of the investigated anomalies. However, aggressively cleaning out data can have an unwanted effect which is overstating the return of the data set as a whole. Specifically, during times with low liquidity, a large amount of stocks with zero return is cleaned out, consequently, the survived stocks have much higher average returns. This effect can be observed through the abnormal return on LSE between the 1830s and 1880s.

3.2 Momentum

I start by forming decile portfolios of stocks based on their conventional momentum in the prior 12 months, excluding the most recent month to account for the short-term reversal effect. The 12M-1M formation period is also one of the most commonly used formation periods in current momentum literature [see e.g. Blitz et al. (2011); Cahart (1997)].

For residual momentum, this research follows the approach in Blitz et al. (2011). Residual returns should be estimated by regressing monthly returns on Fama & French's factors and extracting the residual. However, due to the limitation of data availability where information on book value of stocks and their numbers of share outstanding is mostly inconsistent and incomplete, CAPM is used to estimate residual returns in this research, specifically:

$$r_{i,t} = \alpha_i + \beta_i (R_{m,t} - R_{f,t}) + \varepsilon_{i,t}$$

where $r_{i,t}$ is the excess return of stock i at time t calculated by subtracting the risk-free rate from the total raw return of the stock. $(R_{m,t} - R_{f,t})$ is the market factor, or the excess market return at time t. β_i is the market coefficient of stock I which will be estimated by the model. Finally, $\varepsilon_{i,t}$ is the residual return of stock I at time t and also is the residual momentum used in this research. I then continuously run the regressions over 36-month rolling windows to estimate $\varepsilon_{i,t}$. In order to obtain accurate estimates, only stocks need to have a complete price history in the prior 36 months, otherwise, stocks that have too few observations are excluded from the analysis

For both conventional momentum and residual momentum, stocks are sorted into decile portfolios with the top decile portfolio (D10) contains the top 10 percent of stocks that have the highest conventional momentum (residual momentum) while the bottom decile (D1) contains the lowest. Portfolios are rebalanced monthly and held for different periods ranging from 1 month to 12 months. I also standardize the residual momentum of stocks by dividing them by their standard deviation over the same 36-month period in order to eliminate the noises from raw residual momentum. This approach follows Blitz et al. (2007) which is inspired by Guitierrez and Kelly (2007). Guitierrez and Kelly (2007) argue that standardizing residual momentum improves the measures as firm-specific information. Besides the residual, the market betas estimated from the regressions will also be used in further double-sorting techniques. In regards to the choice of the number of quantile portfolios, having fewer quantiles, for instance terciles, may work better in the early days when the number of stocks available was limited but with a cost that is the return distribution between portfolios is much harder to observe. In this research, I stick to the more common approach which is using decile portfolios, however, the performance of the strategies which utilize tercile portfolios should not be much different from what is found in this research.

Finally, I calculate the post-formation returns over the period for all decile portfolios as well as value-neutral portfolios formed by taking a long position in the top decile portfolio and a short position in the decile portfolio of the respected holding periods. I look at the pre-formation returns, post-formation returns, distribution of returns between portfolios, the statistical significance of these returns in order to draw conclusions to the research. I also test out different holding periods for these portfolios in order to provide a robustness check to the research. The holding period includes 1 month, 3 months, 6 months and 12 months.

3.3 Low volatility

The process of forming decile portfolios for low volatility is similar to that of momentum strategy. At the end of each month, I calculate the monthly volatility of returns of all stocks in the preceding 36 months and put the stocks into portfolios accordingly. The top decile portfolio (D10) consists of stocks with the highest volatility. Similar to momentum strategy, I will also apply double-sorting techniques to low volatility strategy to disentangle low volatility effect from other pricing factors, but only in case of the presence of low volatility effect is found. The process is repeated after every month for the entirety of period, transactions costs are ignored which can be concern about the real profitability of the strategy.

For every decile portfolio, the returns are calculated for different holding periods from 1 month to 12 months. This follows the approach in Blitz et al. (2007) which rebalances stocks every month, but also adds to the robustness of the findings thanks to longer holding periods. Average returns of the portfolios and Sharpe ratio are the benchmark of low volatility strategy's performance in this research.

I also employ a double-sorting methodology in order to separate the volatility effect from other effects when it is needed. Stocks are first ranked on their market beta or conventional momentum and subsequently on volatility within the market beta or momentum groups. This is an empirically robust method to separate these factors from the low volatility effect

3.4 Other factors:

I construct the market return by calculating the equal-weighted return of all stock return on the market at a point of time. This method is commonly used in researches that look far back into the past, such as Geczy and Samanov (2016) and Chabot et al. (2009), because of the availability of data. However, the market factor constructed in this way will underweight big-cap stocks and overweight small-cap stocks.

For the risk-free rate, I use the 10-year government bond yields of the respected markets. Because the data for UK government bonds before 1700 is not available, Dutch government bonds will be used instead for this period. GFD provides the global risk-free rate through their Global government bond yield index. This index is put together by using the yield of the safest government bonds at the time.

4. Empirical results

4.1 Global result

I cannot find sufficient evidence to support the presence of conventional momentum and low volatility anomalies in my global dataset. Specifically, there is no consistency in the performance between decile portfolios and most of the times, the top decile portfolios fail to outperform the bottom decile portfolios which is contradictory to previous literature.

Momentum

In conventional momentum strategy, portfolios with low recent return stocks should underperform high momentum portfolios. It is not the case here as D10 portfolios fail to outperform D1 portfolios in all holding periods. Even though the negative premia are statistically insignificant for most holding periods, they provide enough evidence that conventional momentum is not present in this dataset. Expanding holding periods 12 months makes the return become significant, with the t-stat of -2.54, a reverse-momentum effect seems present in this specific setting.

	Pre-formation return	Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	-0.3773	0.0732	*2.54*	0.0714	*3.76*	0.0500	*3.95*	0.0548	*5.93*
D2	-0.1983	0.0081	*0.37*	0.0044	*0.33*	0.0132	*1.37*	0.0234	*3.22*
D3	-0.1177	0.0300	*1.55*	0.0167	*1.37*	0.0157	*1.79*	0.0167	*2.54*
D4	-0.0567	-0.0228	*-1.11*	0.0229	*1.36*	0.0179	*1.81*	0.0136	*1.98*
D5	-0.0014	0.0304	*1.41*	0.0125	*1.03*	0.0108	*1.22*	-0.0018	*-0.30*
D6	0.0563	0.0391	*1.54*	0.0144	*1.22*	0.0064	*0.76*	0.0023	*0.36*
D7	0.1221	-0.0021	*-0.11*	0.0029	*0.24*	0.0107	*1.09*	0.0030	*0.46*
D8	0.2075	-0.0048	*-0.25*	0.0003	*0.03*	-0.0036	*-0.43*	-0.0038	*-0.63*
D9	0.3475	0.0025	*0.12*	0.0048	*0.38*	0.0031	*0.35*	-0.0040	*-0.65*
D10	0.8704	0.0455	*1.56*	0.0331	*1.90*	0.0339	*2.09*	0.0223	*1.80*
D10-D1		-0.0277	*-0.83*	-0.0384	*-1.90*	-0.0161	*-0.95*	-0.0325	*-2.54*
CAPM's α		-0.0260	*-0.77*	-0.0419	*-2.06*	-0.0180	*-1.06*	-0.0336	*-2.61*

Table 2: Returns of deciles portfolios formed based on momentum with different holding periods for the global dataset. D1 represents the stocks with lowest 36M-1M residual returns while D10 represents the highest. All returns are annualized.

Table 2 shows the performance of momentum portfolios, for all holding periods, most of the returns are concentrated in D1 and D10, which are the two portfolios with the most momentum, albeit in the opposite directions. There is also no apparent pattern in return distribution between

D2 to D9. Since the global dataset is put together by merging data from LSE and NYSE, a possible explanation is there are two strong momentum effects present at the same time which pushes the extreme returns to D1 and D10. This hypothesis will be explored in later parts of this paper which investigate the market in isolation.

Changing the formation periods and holding periods does not improve the results which confirm further there is not one general momentum effect presents during the period with robustness. It is interesting, however, to find another anomalous effect which is similar but completely opposite to the conventional momentum effect.

Residual momentum

Residual momentum is an attempt to disentangle momentum from other pricing factors such as value, size and market factor. Blitz et al. (2011) show that this strategy is able to produce much more consistent returns. In my research, this strategy seems to work to a certain extent. While the result is not identical to that of Blitz et al. (2011), there are some patterns that can be drawn from the strategy.

	Pre-formation return	Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	0.0543	0.0868	*4.08*	0.0528	*3.70*	0.0382	*3.83*	0.0240	*3.29*
D2	0.0890	0.0633	*3.05*	0.0374	*2.77*	0.0332	*3.15*	0.0185	*2.64*
D3	0.0925	0.0451	*2.12*	0.0380	*2.91*	0.0275	*2.96*	0.0179	*2.57*
D4	0.1031	0.0724	*1.80*	0.0202	*1.27*	0.0140	*1.39*	0.0102	*1.45*
D5	0.1030	-0.0051	*-0.24*	0.0075	*0.60*	0.0143	*1.41*	0.0050	*0.74*
D6	0.0725	-0.0205	*-0.97*	0.0047	*0.37*	0.0078	*0.80*	0.0070	*1.03*
D7	0.0597	-0.0141	*-0.67*	0.0021	*0.17*	0.0086	*0.97*	0.0088	*1.34*
D8	0.0477	-0.0080	*-0.40*	-0.0041	*-0.33*	0.0026	*0.29*	0.0114	*1.74*
D9	0.0272	-0.0195	*-0.91*	0.0276	*1.75*	0.0111	*1.15*	0.0120	*1.74*
D10	0.0143	-0.0051	*-0.17*	0.0059	*0.34*	0.0035	*0.31*	0.0141	*1.84*
D10-D1		-0.0920	*-3.03*	-0.0469	*-2.64*	-0.0347	*-3.05*	-0.0099	*-1.31*
CAPM's α		-0.0928	*-3.04*	-0.0461	*-2.59*	-0.0355	*-3.11*	-0.0098	*-1.29*

Table 3: Returns of deciles portfolios formed based on residual momentum with different holding periods for the global dataset. D1 represents the stocks with the lowest 36M-1M residual returns while D10 represents the highest. All returns are annualized

The second column of Table 3 shows that the process of regressing returns on market factors eliminates the characteristics of conventional momentum from the decile portfolios. The top deciles portfolios no longer have the highest pre-formation returns, in fact, the top decile D10 has the lowest momentum prior to its formation.

Remarkably, by sorting stocks by their residual momentum, the resulting decile portfolios now show better patterns of the reverse-momentum effect, which is also found in the previous section, where high residual momentum portfolios generally underperform low residual momentum portfolios.

Firstly, D1 portfolios outperform D10's in all holding periods, the negative excess returns are also significant in three out of four cases. Secondly, although the performances of the portfolios do not decrease monotonically with higher residual momentum, the returns are clearly tilted toward the low residual momentum deciles. While the excess returns from the zero-valued portfolio D10-D1 are negative and significant, it is unclear if this phenomenon presents a real opportunity for profit and more research is needed to confirm this phenomenon.

Extending the holding period reduces the losses of D10-D1 portfolio which may suggest a change in direction when the portfolios are held for a longer period. Still, this result is far from inline with previous research on the matter.

Low volatility

Table 4 continues to show no similarities between expectations and how the investigated anomalies actually work, as once again, the value-neutral portfolios produce negative returns. D1 portfolios underperform D10 portfolios by 9.3% - 12.2% which is completely contradictory to previous findings where low-risk stocks are over-rewarded. Looking at Sharpe ratios of these portfolios also reveals that high-risk stocks actually offer better Sharpe ration than low-risk ones, both pre- and post-formation. Keep in mind that this research deviates from Blitz et al. (2007) which uses weekly stock returns as the measure of volatility due to limited availability of data in the earlier days, especially when it comes to record frequency.

Pre-formation return		K=1			K=3			K=6			K=12		
		Post formation return											
		Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*
D1	0.021	-0.057	*-2.55*	*-0.06*	-0.060	*-5.32*	*-0.12*	-0.056	*-5.53*	*-0.12*	-0.063	*-10.09*	*-0.23*
D2	0.033	-0.038	*-1.98*	*-0.04*	-0.040	*-3.46*	*-0.08*	-0.050	*-6.74*	*-0.15*	-0.054	*-11.36*	*-0.25*
D3	0.031	-0.052	*-3.15*	*-0.07*	-0.049	*-4.86*	*-0.11*	-0.046	*-6.81*	*-0.15*	-0.047	*-9.71*	*-0.22*
D4	0.037	-0.047	*-2.64*	*-0.06*	-0.042	*-3.92*	*-0.09*	-0.039	*-5.19*	*-0.12*	-0.041	*-7.51*	*-0.17*
D5	0.045	-0.033	*-1.68*	*-0.04*	-0.030	*-2.53*	*-0.06*	-0.039	*-4.56*	*-0.10*	-0.037	*-6.03*	*-0.14*
D6	0.051	-0.043	*-2.16*	*-0.05*	-0.039	*-3.08*	*-0.07*	-0.040	*-4.36*	*-0.10*	-0.039	*-5.76*	*-0.13*
D7	0.068	-0.011	*-0.49*	*-0.01*	-0.007	*-0.48*	*-0.01*	-0.006	*-0.61*	*-0.01*	-0.011	*-1.54*	*-0.03*
D8	0.075	0.036	*1.37*	*0.03*	0.035	*2.24*	*0.05*	0.032	*2.85*	*0.06*	0.026	*3.04*	*0.07*
D9	0.095	0.031	*1.20*	*0.03*	0.031	*1.79*	*0.04*	0.023	*1.87*	*0.04*	0.028	*3.09*	*0.07*
D10	0.230	0.055	*1.43*	*0.03*	0.062	*2.53*	*0.06*	0.049	*2.85*	*0.06*	0.029	*2.27*	*0.05*
D1-D10		-0.112	*-2.69*	*-0.06*	-0.122	*-4.90*	*-0.11*	-0.105	*-5.63*	*-0.13*	-0.093	*-6.92*	*-0.16*
CAPM's α		-0.103	*-2.48*		-0.119	*-4.76*		-0.106	*-5.65*		-0.095	*-7.02*	

Table 4: Performances of deciles portfolios formed based on 36-month volatility and one month of holding for the global dataset. D1 represents the stocks with the lowest 36M-1M return volatility while D10 represents the highest. All returns are excess return annualized

Repeating the strategy with different holding periods does not reveal any significant pattern. Therefore, I dismiss the possibility that low volatility effect is present in this data set.

Overall, despite some patterns have been found in this dataset which may or may not present an investing opportunity, without backing from previous literature or good reasonings/explanations for these patterns, I will not go further into this dataset as doing so would push my research more into the region of data mining.

4.2 London Stock Exchange

Analyzing historical stock data for the UK market faces a critical problem: the data itself. I start with more than 2 million observations in my dataset but simple data cleaning techniques quickly reduce the sample down to just under 200,000 observations. The huge number of observations left out presents a high level of illiquidity of the market and low reliability of the record. Therefore, this section needs to be read with these limitations in mind.

Momentum

While signs of the conventional momentum effect are observed in this market, the excess returns of D10-D1 portfolios are not statistically significant in all cases.

	Pre-formation return	Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	-0.3528	0.0568	*1.46*	0.0536	*2.19*	0.0310	*1.77*	0.0554	*4.02*
D2	-0.1783	0.0142	*0.49*	0.0021	*0.12*	0.0052	*0.38*	0.0306	*2.87*
D3	-0.0942	0.0091	*0.36*	0.0047	*0.29*	0.0241	*1.81*	0.0357	*3.54*
D4	-0.0288	0.0095	*0.36*	0.0632	*1.93*	0.0629	*3.50*	0.0488	*4.34*
D5	0.0298	0.0529	*1.25*	0.0616	*3.02*	0.0639	*4.05*	0.0375	*4.03*
D6	0.0877	0.1035	*1.97*	0.0660	*3.21*	0.0727	*4.60*	0.0642	*5.31*
D7	0.1580	0.0575	*2.30*	0.0619	*3.96*	0.0678	*4.26*	0.0607	*6.31*
D8	0.2515	0.1183	*4.53*	0.0796	*4.72*	0.0524	*4.13*	0.0590	*5.57*
D9	0.3946	0.0312	*1.00*	0.0477	*2.58*	0.0595	*4.72*	0.0613	*6.47*
D10	0.9568	0.0693	*1.88*	0.0603	*2.56*	0.0665	*3.84*	0.0639	*5.04*
D10-D1		0.0126	*0.27*	0.0067	*0.23*	0.0355	*1.81*	0.0084	*0.58*
CAPM's α		0.0110	*0.23*	0.0071	*0.24*	0.0368	*1.86*	0.0089	*0.61*

Table 5: Returns of deciles portfolios formed based on momentum with different holding periods for the UK dataset. D1 represents the stocks with the lowest 36M-1M residual returns while D10 represents the highest. All returns are annualized.

The distribution of returns between decile portfolios appears to be random and with no apparent pattern. With most of the t-stats being below 2.0, profiting from momentum investing in this specific market does not seem feasible.

Residual momentum

The result presented in Table 6 is rather uninteresting as little evidence of an anomaly can be found, again. D10 portfolios continue to outperform D1's which is expected from a momentum strategy. However, the possibility of benefitting from this effect is also limited as only one of the t-stats of D1 and D10 portfolios is large enough to conclude a statistical significance.

	Pre-formation return	Post formation return K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	0.0703	0.0260	*0.96*	0.0262	*1.45*	0.0259	*1.41*	0.0174	*1.81*
D2	0.1219	0.0316	*1.02*	0.0326	*1.60*	0.0465	*2.81*	0.0366	*3.08*
D3	0.1226	0.0719	*2.77*	0.0441	*2.49*	0.0506	*3.53*	0.0418	*3.86*
D4	0.1252	0.0788	*2.56*	0.0622	*3.28*	0.0620	*3.80*	0.0588	*5.01*
D5	0.1275	0.0127	*0.44*	0.0277	*1.33*	0.0478	*3.00*	0.0441	*3.90*
D6	0.1032	0.0231	*0.80*	0.0536	*3.02*	0.0461	*3.45*	0.0603	*5.68*
D7	0.0894	0.0191	*0.56*	0.0447	*2.24*	0.0447	*3.05*	0.0403	*3.71*
D8	0.0765	0.0129	*0.39*	0.0460	*1.47*	0.0400	*2.44*	0.0422	*3.77*
D9	0.0563	0.0015	*0.05*	0.0152	*0.81*	0.0277	*1.91*	0.0616	*4.77*
D10	0.0414	0.1505	*1.46*	0.0889	*2.16*	0.0527	*2.24*	0.0613	*4.02*
D10-D1		0.1245	*1.19*	0.0627	*1.48*	0.0268	*1.00*	0.0439	*2.96*
CAPM's α		0.1260	*1.20*	0.0609	*1.42*	0.0283	*1.05*	0.0442	*2.95*

Table 6 Returns of deciles portfolios formed based on residual momentum with different holding periods for the UK dataset. D1 represents the stocks with the lowest 36M-1M residual returns while D10 represents the highest. All returns are annualized.

Among the different holding periods, only K=12 produces a significant excess return. Even so, the weak performances from the other holding periods and the inconsistent distribution of returns between the decile portfolios may suggest future profits from this strategy are uncertain.

Low volatility

The detailed results are shown in Table 7 below. D1-D10 portfolios produce positive returns in all settings. This finding is in line with previous work from Blitz et al. (2007) with two caveats which are the returns in three out of four settings are not statistically significant and the excess returns from the portfolios in the middle do not seem to follow anything particular pattern. For example, D7's and D8's, in some cases, produce positive returns despite all adjacent portfolios' returns are negative.

Pre-formation return		K=1			K=3			K=6			K=12		
		Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*
D1	0.059	0.008	*0.16*	*0.01*	0.003	*0.12*	*0.00*	0.012	*0.54*	*0.02*	0.002	*0.11*	*0.00*
D2	0.060	0.011	*0.26*	*0.01*	0.014	*0.53*	*0.02*	-0.003	*-0.19*	*-0.01*	-0.015	*-1.48*	*-0.05*
D3	0.063	-0.023	*-0.95*	*-0.03*	-0.004	*-0.28*	*-0.01*	-0.005	*-0.45*	*-0.01*	-0.024	*-2.81*	*-0.09*
D4	0.070	-0.013	*-0.51*	*-0.02*	-0.014	*-0.95*	*-0.03*	-0.015	*-1.25*	*-0.04*	-0.018	*-2.05*	*-0.06*
D5	0.088	-0.022	*-0.74*	*-0.02*	-0.026	*-1.57*	*-0.05*	-0.027	*-2.18*	*-0.07*	-0.018	*-1.97*	*-0.06*
D6	0.091	-0.046	*-1.70*	*-0.05*	-0.034	*-1.90*	*-0.06*	-0.029	*-2.17*	*-0.07*	-0.026	*-2.82*	*-0.09*
D7	0.078	0.005	*0.15*	*0.00*	0.001	*0.03*	*0.00*	-0.007	*-0.50*	*-0.02*	-0.009	*-0.79*	*-0.03*
D8	0.097	-0.040	*-1.05*	*-0.03*	-0.006	*-0.24*	*-0.01*	0.008	*0.48*	*0.02*	0.008	*0.71*	*0.02*
D9	0.111	-0.029	*-0.81*	*-0.03*	-0.030	*-1.33*	*-0.04*	-0.028	*-1.63*	*-0.05*	-0.010	*-0.78*	*-0.02*
D10	0.247	-0.061	*-1.08*	*-0.03*	-0.053	*-1.45*	*-0.05*	-0.056	*-2.10*	*-0.07*	-0.030	*-1.64*	*-0.05*
D1-D10		0.069	*0.97*	*0.03*	0.056	*1.37*	*0.04*	0.068	*2.09*	*0.07*	0.032	*1.57*	*0.05*
CAPM's α		0.080	*1.11*		0.063	*1.53*		0.067	*2.02*		0.030	*1.49*	

Table 7: Performances of deciles portfolios formed based on 36-month volatility and one month of holding for the UK dataset. D1 represents the stocks with the lowest 36M-1M return volatility while D10 represents the highest. All returns are excess return and annualized.

Overall, the results display characteristics of the low volatility effect despite the returns being mostly insignificant statistically as highly volatile stocks underperform stable stocks in term both of excess return and Sharpe ratio. Holding periods, on the other hand, do not seem to have much effect on the performance of the strategy.

4.3 New York Stock Exchange

Compared to LSE, data for NYSE is much more complete and reliable which may contribute to the findings of anomalies in this market.

Momentum

The US market is the most extensively investigated market when it comes to anomaly-related research. Most previous literature finds evidence of momentum effect in different periods and stock exchanges. In this section of my work which focuses specifically on NYSE, I also find the momentum effect, but in reverse.

Looking solely at the returns of D10-D1 portfolios presented in Table 8 once again shows signs of a strong reversal effect. All the returns are negative, this means a strategy which long low-momentum stocks and short high-momentum stocks can take advantage of reversal effect. Interestingly, the reversal effect seems to become more significant with longer holding periods, the t-stat jumps from -2.86 with 1-month holding period to -9.45 when the stocks are held for 12 months.

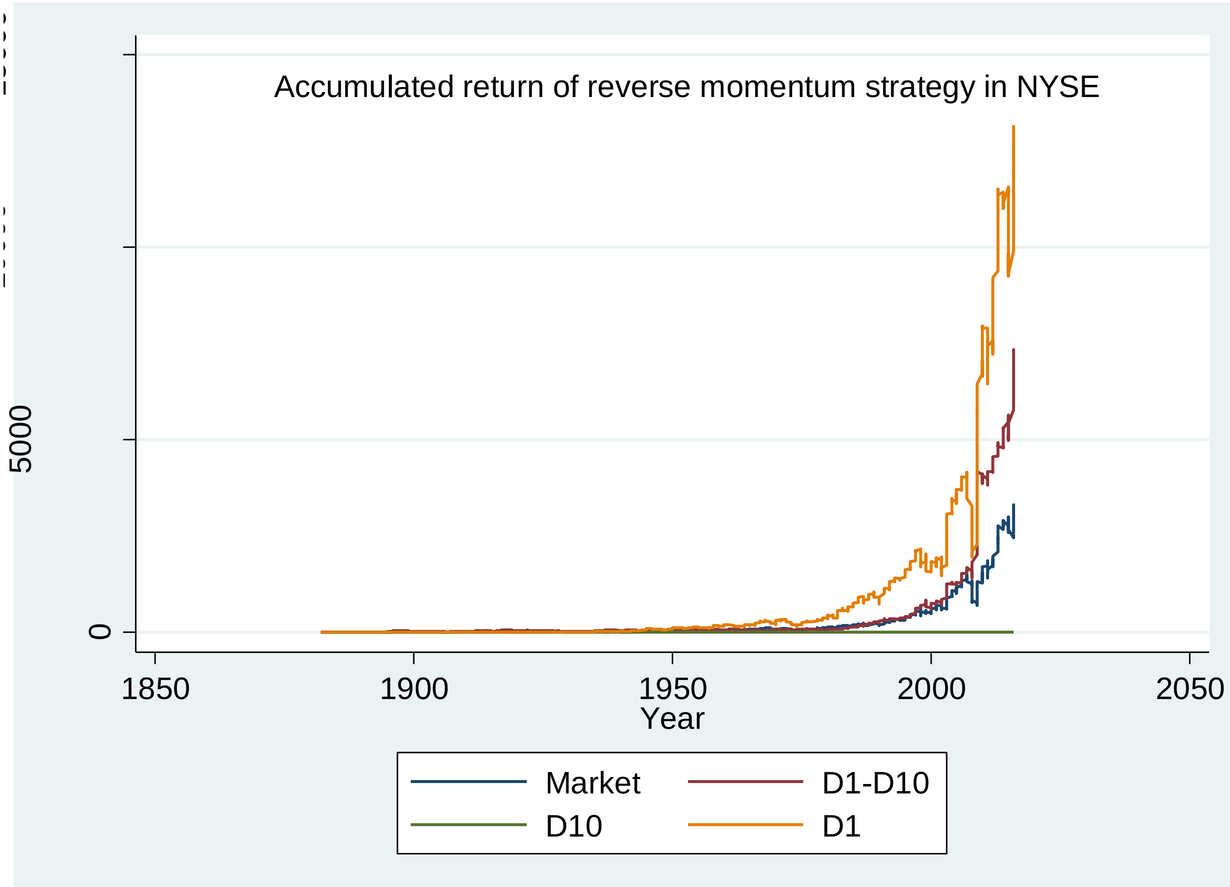
	Pre-formation return	Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	-0.3948	0.1113	*3.12*	0.1017	*4.45*	0.0758	*5.06*	0.0719	*6.72*
D2	-0.2120	0.0544	*1.98*	0.0462	*2.76*	0.0494	*4.04*	0.0572	*6.37*
D3	-0.1274	0.0559	*2.29*	0.0590	*3.74*	0.0613	*5.28*	0.0583	*6.84*
D4	-0.0620	0.0337	*1.46*	0.0409	*2.80*	0.0376	*3.64*	0.0469	*5.85*
D5	-0.0033	0.0302	*1.40*	0.0327	*2.43*	0.0366	*3.63*	0.0392	*5.47*
D6	0.0567	0.0442	*2.11*	0.0548	*3.87*	0.0536	*5.34*	0.0461	*6.24*
D7	0.1243	0.0400	*1.88*	0.0316	*2.33*	0.0264	*2.75*	0.0247	*3.60*
D8	0.2109	0.0221	*0.99*	0.0361	*2.61*	0.0312	*3.12*	0.0276	*3.87*
D9	0.3435	0.0260	*1.09*	0.0221	*1.44*	0.0225	*2.05*	0.0052	*0.71*
D10	0.7739	0.0147	*0.57*	0.0147	*0.92*	0.0134	*1.11*	-0.0109	*-1.37*
D10-D1		-0.0966	*-2.86*	-0.0870	*-4.45*	-0.0624	*-4.97*	-0.0828	*-9.45*
CAPM's α		-0.0957	*-2.82*	-0.0873	*-4.46*	-0.0634	*-5.04*	-0.0832	*-9.48*

Table 8: Returns of deciles portfolios formed based on momentum with different holding periods for the NYSE dataset. D1 represents the stocks with the lowest 36M-1M residual returns while D10 represents the highest. All returns are annualized.

Getting past the D1 portfolio reveals an even more interesting trend. Moving from D1 to D2 shows an abnormal drop off in returns, in some cases, the differences between D1 and D2 portfolios are bigger than the difference between D2 and D10 portfolios. All in all, a momentum strategy, or rather a reverse-momentum strategy in this case, would produce an average return between 6.2% and 9.7% annually with a minimum t-stat of -2.86.

Between D1 and D10, the reversal effect is pronounced for all holding periods. While there are still some irregularities, the general trend can be found here is the higher momentum prior to formation leads to worse performances after that. In an extreme case (K=12), the average return of D10 portfolio is even negative.

Overall, the NYSE shows a completely opposite effect of the conventional momentum effect where high-momentum portfolios are expected to outperform low-momentum portfolios. While irregularities are not uncommon and have been well-recorded in previous literature, for the time being, I cannot find a conclusive explanation for this phenomenon. This could be a result of a combination of factors ranging from data processing to seasonality, cyclicality of momentum effect or some market characteristics which are specific to the NYSE.



Graph 1: Accumulated return of reverse momentum strategy. D1 consists of stocks with the lowest past return, D10 consists stocks with the highest past return. D1-D10 is the value-neutral portfolio which represents the strategy.

Residual momentum and double sorting technique

Blitz et al. (2011) show that residual momentum has better performance and consistency than conventional momentum. In this case, residual momentum strategy seems to reduce the negative effect of the conventional momentum effect which is found in the previous section. Unfortunately, while the losses are reduced, statistical significances of the returns are also lost. Detailed result is shown in Table 9 below.

For the first three shortest holding periods, D10-D1 portfolios produce insignificant negative returns. This is inconsistent with previous literature on residual momentum which should produce positive returns in these very short holding periods. The performances of the D10 portfolios, however, are improved significantly while D1 portfolios also lose a considerable amount of returns compared to conventional momentum strategy.

	Pre-formation return	Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	0.0807	0.0503	*1.96*	0.0461	*2.93*	0.0422	*3.58*	0.0334	*4.23*
D2	0.0919	0.0428	*1.68*	0.0533	*3.47*	0.0463	*4.10*	0.0389	*4.80*
D3	0.0912	0.0652	*2.52*	0.0627	*3.77*	0.0547	*4.71*	0.0448	*5.26*
D4	0.0872	0.0448	*1.61*	0.0408	*2.46*	0.0434	*3.63*	0.0396	*4.77*
D5	0.0847	0.0675	*2.81*	0.0575	*3.58*	0.0472	*4.20*	0.0453	*5.49*
D6	0.0612	0.0434	*1.81*	0.0383	*2.49*	0.0471	*3.93*	0.0479	*5.47*
D7	0.0561	0.0289	*1.21*	0.0446	*2.77*	0.0472	*4.28*	0.0379	*4.74*
D8	0.0457	0.0369	*1.46*	0.0497	*3.01*	0.0373	*3.23*	0.0359	*4.41*
D9	0.0283	0.0411	*1.71*	0.0405	*2.55*	0.0428	*3.87*	0.0466	*5.61*
D10	0.0233	0.0370	*1.41*	0.0310	*1.96*	0.0279	*2.50*	0.0383	*4.46*
D10-D1		-0.0133	*-0.49*	-0.0151	*-1.04*	-0.0143	*-1.35*	0.0049	*0.62*
CAPM's α		-0.0130	*-0.47*	-0.0153	*-1.04*	-0.0141	*-1.33*	0.0058	0.73

Table 9: Returns of deciles portfolios formed based on residual momentum with different holding periods for the NYSE dataset. D1 represents the stocks with the lowest 36M-1M residual returns while D10 represents the highest. All returns are annualized

The effect of changing holding periods on the returns of the zero-valued portfolios is vague. Although extending the holding period to 12 months changes the sign of the excess return in D10-D1 portfolios from negative to positive, the return is very negligible at only 0.5%. After all, the returns of D10-D1 portfolios are insignificant statistically, and therefore no conclusion can be drawn in this case.

Despite the improved performance in D10-D1 portfolios compared to conventional momentum strategy, the strange distribution of returns in middle deciles persists. Most of the returns are concentrated in the middle portfolios instead of the portfolios on either end, there is not one portfolio that outperforms other portfolios consistently across different holding periods.

Along with residual momentum, another method to decouple market beta from momentum effect is double sorting, which ranks stocks into quintile portfolios based on their market beta first then ranks the stocks within the quintile portfolios based on their conventional momentum.

	Pre-formation return	Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
D1	-0.2614	0.0653	*2.60*	0.0609	*3.80*	0.0565	*4.94*	0.0611	*7.26*
D2	-0.0668	0.0406	*1.86*	0.0461	*3.24*	0.0455	*4.54*	0.0480	*6.66*
D3	0.0485	0.0517	*2.57*	0.0518	*3.92*	0.0458	*4.85*	0.0434	*6.37*
D4	0.1843	0.0282	*1.37*	0.0355	*2.66*	0.0306	*3.26*	0.0229	*3.40*
D5	0.5116	0.0233	*1.05*	0.0234	*1.73*	0.0214	*2.14*	0.0030	*0.44*
D5-D1		-0.0420	*-2.23*	-0.0375	*-3.56*	-0.0351	*-4.81*	-0.0581	*-11.56*
CAPM's α		-0.0402	*-2.14*	-0.0372	*-3.52*	-0.0351	*-4.81*	-0.0583	*-11.57*

Table 10: Returns of deciles portfolios formed based on market beta and momentum with different holding periods for the NYSE dataset. Stocks are first sorted into quintile portfolios based on their market beta from the preceding 36 months. Stocks in each quintile portfolio are then ranked by their 12M-1M momentum. Quintile momentum portfolios with the same rank are put together to form D1 to D5 with D5 represents highest momentum stocks and vice-versa. All returns are annualized

Pre-formation performances of portfolios are the striking difference between double sorting strategy and residual momentum strategy, which can be seen in the second column of Table 9 and 10. In residual momentum strategy, there is virtually no pattern in the pre-formation returns between portfolios, high residual momentum portfolios can have low momentum and vice-versa. Contrary to residual momentum, pre-formation returns increase monotonically when moving from bottom quintiles to higher quintiles.

The post-formation returns of the double sorting strategy share more similarities to those of conventional momentum than residual momentum, which is strange considering residual momentum and double-sorting are both intended to disentangle market beta from momentum. D10-D1 portfolios record a negative return in all holding period with all t-stats being well below the cut-off point of -2.0. The general distribution of returns between quintile further confirms the existence of a reverse momentum effect where bottom portfolios outperform top portfolios.

Overall, my approach deviates from the approach in Blitz et al. (2011), which potentially is the cause of the huge differences between the results. Accounting for size and value effects can help to improve the results, unfortunately, these kinds of data are not available at a reasonable level of reliability and completeness for the time being. With the results shown in this section, residual momentum can be argued as an improvement over conventional momentum due to higher excess returns of the value-neutral portfolios, unfortunately, this kind of improvement offers no investment opportunity. The double-sorting technique, on the other hand, presents a real opportunity for investors who look to invest in a momentum-based, market-neutral strategy.

Low volatility

Instead of finding a conventional low volatility effect, I find a reverse effect, where post-formation returns increase virtually monotonically with pre-formation return volatility i.e. highly volatile stocks yield higher excess return and vice-versa. This phenomenon is also consistent in all holding periods. While this finding does not violate the market efficiency where high risks are rewarded with high rewards, it is the complete opposite of low volatility anomaly which is a well-known anomaly by itself.

	Pre-formation return	Post formation return											
		K=1			K=3			K=6			K=12		
		Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*
D1	0.023	-0.051	*-3.70*	*-0.09*	-0.056	*-6.47*	*-0.16*	-0.058	*-9.17*	*-0.23*	-0.050	*-10.97*	*-0.28*
D2	0.040	-0.039	*-2.42*	*-0.06*	-0.036	*-3.54*	*-0.09*	-0.037	*-5.01*	*-0.13*	-0.043	*-7.50*	*-0.19*
D3	0.045	-0.007	*-0.39*	*-0.01*	-0.007	*-0.59*	*-0.01*	-0.015	*-1.87*	*-0.05*	-0.016	*-2.70*	*-0.07*
D4	0.049	-0.019	*-0.90*	*-0.02*	-0.013	*-0.98*	*-0.02*	-0.009	*-0.95*	*-0.02*	-0.011	*-1.48*	*-0.04*
D5	0.053	-0.010	*-0.44*	*-0.01*	-0.007	*-0.46*	*-0.01*	-0.014	*-1.33*	*-0.03*	-0.016	*-1.99*	*-0.05*
D6	0.063	0.012	*0.47*	*0.01*	0.017	*1.11*	*0.03*	0.022	*1.84*	*0.05*	0.016	*1.87*	*0.05*
D7	0.073	0.026	*0.92*	*0.02*	0.020	*1.12*	*0.03*	0.017	*1.31*	*0.03*	0.018	*1.96*	*0.05*
D8	0.061	0.033	*1.09*	*0.03*	0.035	*1.84*	*0.05*	0.036	*2.59*	*0.07*	0.026	*2.59*	*0.07*
D9	0.085	0.028	*0.85*	*0.02*	0.028	*1.23*	*0.03*	0.023	*1.46*	*0.04*	0.026	*2.24*	*0.06*
D10	0.168	0.041	*0.97*	*0.02*	0.037	*1.46*	*0.04*	0.032	*1.71*	*0.04*	0.008	*0.64*	*0.02*
D1-D10		-0.092	*-2.35*	*-0.06*	-0.093	*-4.05*	*-0.10*	-0.090	*-5.24*	*-0.13*	-0.058	*-5.15*	*-0.13*
CAPM's α		-0.087	*-2.23*		-0.090	*-3.91*		-0.089	*-5.18*		-0.058	*-5.17*	

Table 11: Performances of deciles portfolios formed based on 36-month volatility and one month of holding for the NYSE dataset. D1 represents the stocks with lowest 36M-1M return volatility while D10 represents the highest. All returns are excess returns and annualized.

The first interesting pattern to notice is the pre-formation returns of the decile portfolios which is shown in the second column of Table 11. Although the stocks are ranked by their preceding 36-month volatility, the pre-formation returns show signs of momentum as they increase virtually monotonically with volatility. D1 portfolios have the average pre-formation return as low as 2.3% a year while the past return of D10's is an amazing 16.8%. This reveals a connection between volatility and momentum of stocks, specifically on NYSE, although the exact mechanism of this connection has not been agreed among researchers.

The expectation for low volatility is high-risk stocks would underperform compared to low-risk stocks, however, it is not the case here. High risks are rewarded with high reward, bar a few exceptions, this pattern is consistent across all decile portfolios and for all holding periods. Even after accounting for risk, high-risk portfolios still produce superior Sharpe ratio.

In order to profit from the low volatility, contrary to Blitz et al. (2007), investors would need to short low volatile portfolios and long a highly volatile portfolio, the resulting zero-valued portfolio would produce between 5.8% to 9.2% of statistically significant excess return depending on the choice of portfolios and holding duration.

Since the finding is not consistent with previous literature and seems specific only to NYSE, more researches are needed to confirm the nature and validity of this anomaly.

	Pre-formation return	Post formation return											
		K=1			K=3			K=6			K=12		
		Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*
D1	0.046	-0.029	*-1.89*	*-0.05*	-0.033	*-3.31*	*-0.08*	-0.036	*-5.03*	*-0.13*	-0.035	*-6.51*	*-0.16*
D2	0.056	-0.012	*-0.60*	*-0.02*	-0.010	*-0.84*	*-0.02*	-0.016	*-1.77*	*-0.04*	-0.019	*-2.92*	*-0.07*
D3	0.060	0.004	*0.19*	*0.00*	0.004	*0.27*	*0.01*	0.000	*0.02*	*0.00*	-0.010	*-1.31*	*-0.03*
D4	0.072	0.013	*0.53*	*0.01*	0.014	*0.82*	*0.02*	0.010	*0.85*	*0.02*	0.009	*1.05*	*0.03*
D5	0.098	0.006	*0.18*	*0.00*	0.019	*0.92*	*0.02*	0.025	*1.61*	*0.04*	0.021	*1.90*	*0.05*
D1-D5		-0.035	*-1.44*	*-0.04*	-0.052	*-3.42*	*-0.09*	-0.061	*-5.34*	*-0.14*	-0.055	*-7.20*	*-0.18*
CAPM's α		-0.033	*-1.34*		-0.051	*-3.34*		-0.061	*-5.34*		-0.055	*-7.21*	

Table 12: Returns of deciles portfolios formed based on momentum and volatility with different holding periods for the NYSE dataset. Stocks are first sorted into quintile portfolios based on their momentum from the preceding 12M-1M period. Stocks in each quintile portfolio are then ranked by their 36M-1M volatility. Quintile volatility portfolios with the same rank are put together to form D1 to D5 with D5 represents highest volatility stocks and vice-versa. All returns are excess returns and annualized

Because the low volatility decile portfolios demonstrate characteristics of momentum effect, disentangling momentum from volatility would help to highlight the real effect of low volatility. One of the techniques to do so is double sorting, in which, stocks are first ranked based on their momentum then are ranked on low volatility.

Evidently, double-sorting helps reduce the disparity in pre-formation momentum between the quintile portfolios (see Table 12, second row), which may suggest the two effects are related to each other to a certain extent.

In general, the returns from this strategy is fairly similar to those from low volatility strategy, which confirms that the pattern of returns found in low volatility strategy is not a result of entanglement between low volatility and momentum. High volatility portfolios outperform low volatility portfolios in terms of both excess return and Sharpe ratio. Different from residual momentum, holding periods seem to have a noticeable effect on the performance of market beta-momentum double sorting strategy. While longer holding periods may not increase the excess returns, they do improve the significance. At K=12, the strategy produces -5.5% of excess return annually with a very high t-stat of -7.20. How long before the trend reverses, however, is not investigated in this research.

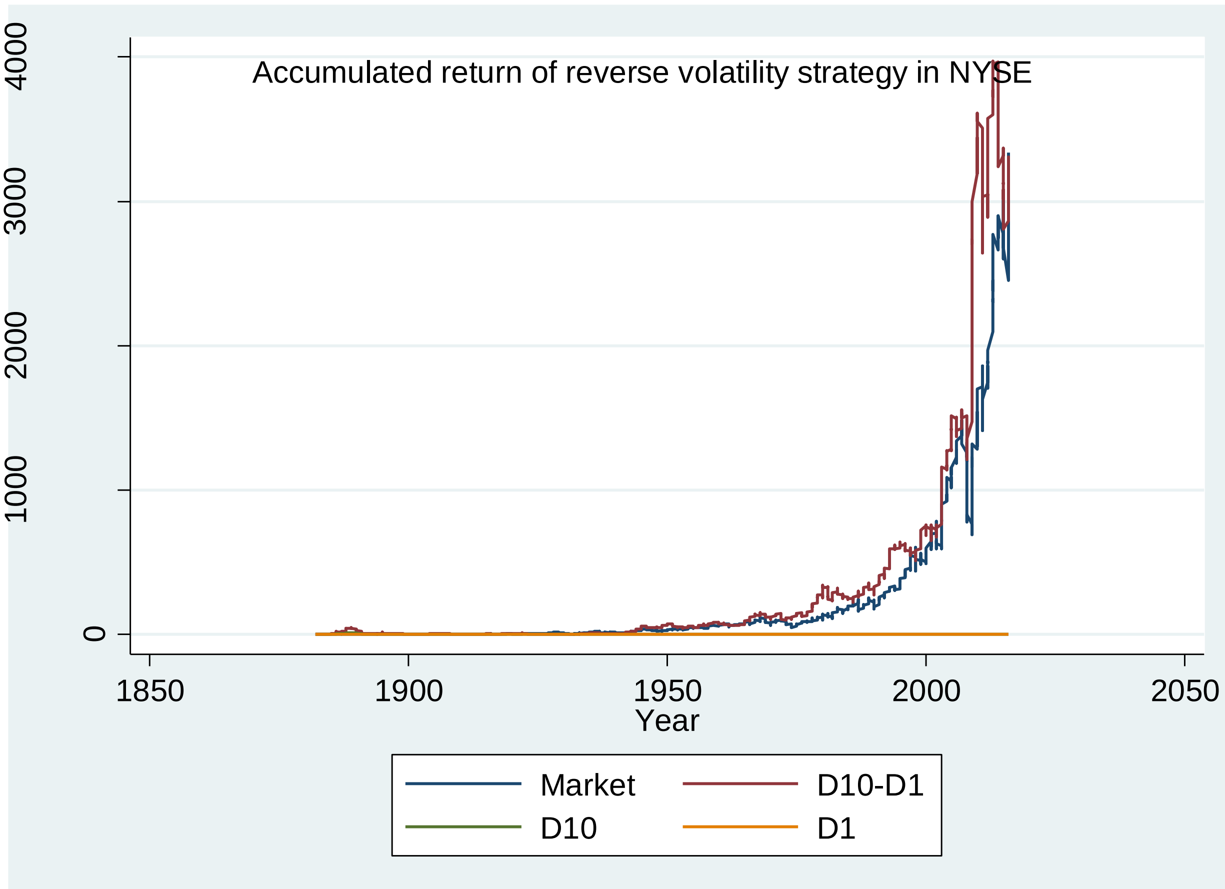
Another criticism of the low volatility strategy is that ranking stocks based on their volatility can be similar to ranking them based on their market beta. For instance, when the market is in a highly volatile state, stocks with high market betas would record a high level of volatility and vice-versa. Double-sorting stocks based on their market beta and volatility can help examine this concern. Table 13 shows the results.

	Pre-formation return	Post formation return											
		K=1			K=3			K=6			K=12		
		Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*	Return	*t-value*	*Sharpe*
D1	0.050	-0.009	*-0.47*	*-0.01*	-0.005	*-0.44*	*-0.01*	-0.009	*-1.08*	*-0.03*	-0.012	*-1.93*	*-0.05*
D2	0.057	-0.003	*-0.13*	*0.00*	-0.003	*-0.23*	*-0.01*	-0.003	*-0.37*	*-0.01*	-0.007	*-1.00*	*-0.03*
D3	0.059	-0.003	*-0.16*	*0.00*	0.002	*0.12*	*0.00*	0.002	*0.22*	*0.01*	-0.004	*-0.52*	*-0.01*
D4	0.069	0.004	*0.16*	*0.00*	0.000	*0.02*	*0.00*	-0.006	*-0.52*	*-0.01*	-0.005	*-0.63*	*-0.02*
D5	0.100	0.007	*0.23*	*0.01*	0.017	*0.90*	*0.02*	0.016	*1.14*	*0.03*	0.009	*0.91*	*0.02*
D1-D5		-0.015	*-0.69*	*-0.02*	-0.022	*-1.67*	*-0.04*	-0.025	*-2.55*	*-0.06*	-0.021	*-2.99*	*-0.08*
CAPM's α		-0.012	*-0.53*		-0.020	*-1.5*		-0.024	*-2.42*		-0.021	*-2.91*	

Table 13: Returns of deciles portfolios formed based on market beta and volatility with different holding periods for the NYSE dataset. Stocks are first sorted into quintile portfolios based on their market beta from the preceding 36 months. Stocks in each quintile portfolio are then ranked by their 36M-1M volatility. Quintile volatility portfolios with the same rank are put together to form D1 to D5 with D5 represents highest volatility stocks and vice-versa. All returns are excess returns and annualized

Evidently, the reverse low volatility effect becomes less pronounced after neutralizing market beta as both the returns of the value-neutral portfolios and their t-stats are greatly reduced. The average returns of D5-D1 portfolios are now between 1.5% and 2.5%. However, the general pattern persists as high volatility portfolios continue to outperform low volatility portfolio. The market also seems to over-reward risky stocks and over-punish safer stocks which is reflected in the Sharpe ratios.

Once again, this pattern is contrary to the low volatility effect found in Blitz et al. (2007) but complies with the market efficiency theory. In terms of accumulated returns (see Graph 2), while the accumulated returns of D1 and D10 portfolios are insignificantly low, the excess return from D10-D1 portfolio manages to outperform the market return during the period.



Graph 2: Accumulated return of reverse volatility strategy. D1 consists of stocks with lowest past return volatility, D10 consists stocks with highest past return volatility. D10-D1 is the value-neutral portfolio which represents the strategy.

In conclusion, while certain strategies can produce an excess return with statistical significance, the lack of uniform patterns among portfolios' returns leads me to believe that there is not one momentum strategy that persists during the entire period. This conclusion, however, does not deny the existence of all momentum effects altogether. Instead, there can be different momentum effects that exist during different periods and with different characteristics (see Appendix for an investigation of these anomalies in 50-year sub-samples). This inconsistency of momentum poses a risk to momentum investing as identifying future's momentum trends is not an easy task.

For the low volatility anomaly, it is interesting to find the presence of the low volatility effect, but in another direction. Contrary to Blitz et al. (2007) which finds out the market tends to under-reward high-risk stocks and vice-versa, in my work in NYSE, high-risk stocks are highly rewarded with positive excess returns and Sharpe ratios. Specifically, a theoretical trading strategy involving buying high-risk stocks and selling low-risk stocks can be profitable. The profits are robust for different holding periods as well as different formation periods. Another reason to believe there is a reverse low volatility effect is the consistency of return patterns, moving from lower risk portfolios to higher risk portfolios improves the excess returns virtually monotonically. Furthermore, momentum and market beta are found to be contributing factors to the returns of the reverse low volatility effect in my research, however, after accounting for these factors, the returns still persist with robustness and statistical significance. My findings, once again, do not deny the presence of the conventional low volatility effect at certain periods of time or with different settings or market. Instead, my findings highlight the uncertain nature of anomalies which can change and will change in an unpredictable way in the future, and hence, profiting from anomalous investing remains a challenge for investors and researchers.

5. Discussion

While my work is inspired by a number of papers about market anomalies, I do not strictly follow the approaches in these papers when carrying out my research because of reasons including data unavailability and feasibility of the scope of work. As a result, the findings are not expected to be identical to those of earlier works. Because of the substantial differences discovered in the previous section, this section will attempt to bridge the huge gap between my research and the existing literature on the matter.

The first potential source of the differences is the period of investigation, instead of focusing on a specific period of time, I attempt to examine the anomalies during the whole history of NYSE and LSE, two of the biggest and most important stock exchanges in the world. As the markets worked in a very different way in their early days compared to what they are today, without breaking down the long period into smaller sub-period, the noises from historical events and changes may have driven out the effect of anomalies. This explanation is supported by various researches which investigate how anomalies change over the years, notably, Barroso and Santa-Clara (2013) argue that momentum returns have a distribution far from normal and are exposed to huge crash risk, this claim is further supported by Daniel and Moskowitz (2012) when they discover a number of momentum crashes during the history and Cooper et al. (2004) when they investigate the relationship between market states and momentum.

The choice of market is another potential contributing factor to the differences found in my research. Asness (2011) discovers no momentum effect in the Japanese market which poses a question whether these anomalies are characters of certain markets or it is a universal effect in investment. Therefore, my choice of markets (NYSE and LSE) that deviates from other literature, which tends to investigate the US market or European market as a whole, could be a cause for the differences. However, my findings can be valuable for investors with a narrow focus on a few stock exchanges and want to profit from anomaly investing.

The reliability of data sources from the early day also needs to be put into question. Without modern technologies, data from the early days are all collected and recorded by hands which represents an inevitable risk of human errors. Missing observations and abnormal values are not rare occurrences in these data records, once the data is broken there is little researchers can do to recover these data with reasonable reliability. There was also not a uniform system of data recording. Data can be collected at different frequency from weekly to monthly, even 28-day cycle in some periods. Stocks can be included and excluded at a whim. Therefore, putting together complete data set for a period this long is very difficult, especially with consistency and reliability of the data as the main concerns. With all these shortcomings from the data, all findings from the era must be concluded with caution.

Minor specifics of a trading strategy can play a great role in the final outcome, specifically the portfolio formation process. Asness et al. (2014) confirm that different measures of momentum can give different result over different periods. In my research, I follow a standard approach of sorting the stocks into 10 decile portfolios for single-sorting strategies and 5 quintile portfolios for double-sorting strategies. This approach is similar to Jegadeesh and Titman (1993, 2001) Blitz et al. (2007), Blitz et al. (2011) and many others. However, researches in this field can choose to sort the stocks into three equal quantiles portfolio to eliminate the noises and make the research process simpler in sacrifice of the magnitude of the anomalous effects. One notable research that uses this approach is Geczy and Samonov (2016) which finds evidence of momentum effect in the US market for a prolonged period. Similarly, due to data unavailability, I have to use monthly volatility instead of weekly volatility as in the original work of Blitz et al. (2007).

Last but not least, data cleaning has always been a challenge to every research that aims to investigate a big data set, and my research is no exception. The choice of which data cleaning techniques will be used has a huge influence on the final outcome. Many times, there are more than one possible way to clean the data, among which no approach is clearly superior to others. For example, I use $5 as the threshold for micro stocks, stocks that are priced below this point are excluded from the data set. This threshold is commonly used in researches in this field [see e.g. Blitz et al. (2011), Jegadeesh and Titman (1993), Asness et al. (2011) and others]. However, because of the changing value of the currency over the time, a $5 stock in the 1800s may not be a micro stock as it would be today.

6. Conclusion

Instead of finding pronounced and consistent anomalies, in my work, I can only find fractions of these anomalies here and there. Sometimes, the anomalous effects also work in the reverse way, to which very few explanations can be found. Specifically, the only anomalous effect I find with consistency and robustness in my research is a reverse effect of low volatility for NYSE, when high-risk stocks continuously outperform low-risk stocks. Some signs of (reverse-) momentum and residual momentum effects are also found in NYSE but with the lower magnitude and without a consistent pattern. For LSE, the data seems incomplete and unreliable which is highlighted by a large number of observations being cleared out during the data cleaning process. This can be a reason that I only find noises instead of any pronounced effect in the remaining data set. These noises are also carried over to the global dataset and therefore, no interesting findings are discovered.

Regarding my findings, there are a few possible explanations for the huge difference compared to previous literature. Firstly, the prolonged period of investigation may have canceled out the presence of one uniform anomaly, instead, their existences can be hidden in smaller sub-periods. Next, the reliability of the data is also questionable as human errors were much more prevalent in the early days when data was collected by hands. The unreliable and missing data then forces the research to deviate from existing literature in order to mitigate these concerns. Finally, data cleaning is a huge challenge when the data set is this big, papers in this field rarely specify their data processing procedure in detail and completeness, and hence prevents later works to replicate the same exact results.

Since the ways these anomalies work differ greatly from period to period and from market to market, we all can expect them to continue to change in the future. And therefore, profiting from anomaly investing will never be truly riskless.

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APPENDIX

Sub-sample analysis

Table A.1 to A.9 below show the performances of the anomalies in different 50-year periods. The purpose of this section is to show how the anomalies changed over time, and to a certain extent, these changes also reflect the changes in data availability and reliability during the same period of time. The most important takeaway from this section is further confirmation that the ways these strategies work are specific to the markets and the periods of time, and if there are no ways to reliably predict how these strategies would change in the future, investing in these strategies should not be considered risk-free.

Global results:

There are clear differences in performances between the sub-samples, both in terms of magnitude and significance. The strategies seem to gain a lot of statistical significance in the last two sub-samples, 1918-1967 and 1968-2017, which makes sense since these strategies were discovered in the modern era and stock markets were different in the early days. Despite the differences, these strategies still produce negative return bar only a few exceptions, which is unexpected given the existing literature on the matter.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1867	D10-D1	0.413	*1.79*	0.307	*2.41*	0.350	*2.59*	0.325	*3.20*
	CAPM's α	0.437	*1.83*	0.311	*2.34*	0.361	*2.57*	0.327	*3.10*
1868-1917	D10-D1	-0.140	*-2.08*	-0.147	*-3.35*	-0.090	*-3.02*	-0.063	*-2.82*
	CAPM's α	-0.144	*-2.12*	-0.151	*-3.40*	-0.094	*-3.12*	-0.064	*-2.84*
1918-1967	D10-D1	-0.009	*-0.21*	-0.013	*-0.51*	-0.009	*-0.61*	-0.071	*-6.16*
	CAPM's α	-0.007	*-0.17*	-0.017	*-0.67*	-0.011	*-0.73*	-0.071	*-6.16*
1968-2017	D10-D1	-0.073	*-2.96*	-0.065	*-4.31*	-0.065	*-5.75*	-0.077	*-9.92*
	CAPM's α	-0.069	*-2.79*	-0.064	*-4.26*	-0.065	*-5.67*	-0.077	*-9.88*

Table A.1: Momentum returns of the global data set in different 50-year sub-periods.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1867	D10-D1	0.085	*0.34*	-0.079	*-0.61*	-0.095	*-1.31*	-0.093	*-2.27*
	CAPM's α	0.112	*0.44*	-0.065	*-0.49*	-0.090	*-1.19*	-0.093	*-2.19*
1868-1917	D10-D1	-0.050	*-0.99*	-0.021	*-0.58*	-0.014	*-0.57*	0.006	*0.34*
	CAPM's α	-0.060	*-1.18*	-0.022	*-0.61*	-0.016	*-0.63*	0.005	*0.28*
1918-1967	D10-D1	-0.144	*-4.31*	-0.043	*-2.26*	-0.033	*-2.30*	0.000	*-0.02*
	CAPM's α	-0.141	*-4.22*	-0.041	*-2.15*	-0.032	*-2.27*	0.001	*0.12*
1968-2017	D10-D1	-0.138	*-8.11*	-0.066	*-6.32*	-0.038	*-5.20*	-0.009	*-1.87*
	CAPM's α	-0.141	*-8.22*	-0.068	*-6.54*	-0.041	*-5.67*	-0.011	*-2.25*

Table A.2: Residual momentum returns of the global data set in different 50-year sub-periods.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1867	D1-D10	-0.295	*-1.29*	-0.245	*-1.82*	-0.175	*-1.99*	-0.043	*-0.97*
	CAPM's α	-0.301	*-1.27*	-0.246	*-1.76*	-0.181	*-1.98*	-0.054	*-1.16*
1868-1917	D1-D10	-0.080	*-0.82*	-0.118	*-2.00*	-0.091	*-1.88*	-0.109	*-2.90*
	CAPM's α	-0.071	*-0.72*	-0.113	*-1.89*	-0.088	*-1.81*	-0.112	*-2.95*
1918-1967	D1-D10	-0.124	*-2.20*	-0.131	*-3.82*	-0.128	*-5.43*	-0.116	*-6.99*
	CAPM's α	-0.119	*-2.12*	-0.130	*-3.80*	-0.130	*-5.52*	-0.117	*-7.00*
1968-2017	D1-D10	-0.073	*-2.47*	-0.079	*-4.13*	-0.076	*-5.45*	-0.068	*-7.56*
	CAPM's α	-0.062	*-2.14*	-0.076	*-3.98*	-0.077	*-5.51*	-0.070	*-7.67*

Table A.3: Low volatility returns of the global data set in different 50-year sub-periods.

LSE results:

Despite being mostly insignificant statistically, a lot of returns in the first three sub-periods can be considered abnormal which highlights the fact that stock data of LSE in the pre-Datastream era (before 1965) is highly unreliable with many unrecoverable missing points and suspicious values. Aggressive cleaning is necessary to deal with the problem but it comes with an unwanted effect that the data now suffers from some kind of survivorship bias, in which the 'survived' stocks are not necessarily the better performers but rather ones that happen to have higher quality in data recording. Even when setting aside the data problem and looking solely at the last sub-period (1968-2017), in which the data is more reliable and complete, not many signs of the anomalies can be found. Most of the results are either insignificant or contrary to previous literature or both. The lack of consistency of the results is too much to conclude anything with reasonable certainty.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1867	D10-D1	0.281	*1.35*	0.205	*1.56*	0.129	*1.34*	-0.015	*-0.24*
	CAPM's α	0.301	*1.40*	0.236	*1.75*	0.139	*1.41*	-0.028	*-0.43*
1868-1917	D10-D1	-0.081	*-0.82*	-0.088	*-1.39*	-0.031	*-0.84*	0.037	*1.69*
	CAPM's α	-0.085	*-0.86*	-0.095	*-1.47*	-0.036	*-0.95*	0.037	*1.68*
1918-1967	D10-D1	-0.394	*-1.67*	-0.376	*-2.96*	-0.134	*-1.06*	0.017	*0.23*
	CAPM's α	-0.386	*-1.51*	-0.350	*-2.57*	-0.154	*-1.13*	0.013	*0.16*
1968-2017	D10-D1	0.026	*0.51*	0.032	*1.02*	0.058	*2.65*	-0.002	*-0.09*
	CAPM's α	0.024	*0.48*	0.032	*1.03*	0.061	*2.76*	0.001	*0.03*

Table A.4: Momentum returns of the LSE data set in different 50-year sub-periods.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1867	D10-D1	0.246	*0.80*	0.143	*1.04*	0.034	*0.41*	-0.038	*-0.81*
	CAPM's α	0.255	*0.80*	0.135	*0.95*	0.037	*0.42*	-0.045	*-0.92*
1868-1917	D10-D1	0.252	*0.77*	0.113	*0.93*	0.004	*0.05*	0.020	*0.55*
	CAPM's α	0.253	*0.76*	0.116	*0.95*	0.010	*0.12*	0.019	*0.51*
1918-1967	D10-D1	0.344	*1.07*	-0.538	*-0.90*	-0.046	*-0.14*	-0.107	*-0.59*
	CAPM's α	-0.087	*-0.23*	-0.457	*-0.52*	-0.060	*-0.12*	-0.308	*-1.31*
1968-2017	D10-D1	0.038	*0.88*	0.031	*1.03*	0.038	*2.08*	0.072	*4.78*
	CAPM's α	0.039	*0.91*	0.029	*0.96*	0.038	*2.06*	0.073	*4.84*

Table A.5: Residual momentum returns of the LSE data set in different 50-year sub-periods.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1867	D1-D10	-0.091	*-0.26*	-0.136	*-0.71*	-0.080	*-0.75*	-0.022	*-0.38*
	CAPM's α	0.004	*0.01*	-0.095	*-0.48*	-0.073	*-0.66*	-0.021	*-0.34*
1868-1917	D1-D10	0.319	*1.77*	0.272	*3.13*	0.354	*4.54*	0.242	*5.48*
	CAPM's α	0.312	*1.72*	0.271	*3.09*	0.339	*4.33*	0.236	*5.31*
1918-1967	D1-D10	-0.092	*-0.24*	0.145	*0.58*	0.455	*2.50*	0.429	*139.20*
	CAPM's α	-0.154	*-0.27*	0.007	*0.02*	0.288	*1.17*	0.430	*95.75*
1968-2017	D1-D10	-0.023	*-0.44*	-0.018	*-0.44*	-0.050	*-1.52*	-0.067	*-2.95*
	CAPM's α	-0.018	*-0.35*	-0.014	*-0.35*	-0.050	*-1.50*	-0.068	*-2.97*

Table A.6: Low volatility returns of the LSE data set in different 50-year sub-periods.

NYSE results:

Compared to LSE, NYSE is a relatively newer stock exchange and therefore, its data set can only be divided into three sub-periods. Expectedly, the strongest and most significant presences of the anomalies are found in the last sub-period between 1968 and 2017. These anomalous effects can also be found in the other two sub-samples but with varied significances and magnitudes. Negative is the sign of virtually all returns from conventional momentum and low volatility strategies across all sub-samples. More positive returns are found from residual momentum strategy but negatives are still ones with highest significances.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1917	D10-D1	-0.235	*-1.99*	-0.192	*-2.91*	-0.105	*-2.42*	-0.101	*-3.52*
	CAPM's α	-0.237	*-2.01*	-0.189	*-2.87*	-0.107	*-2.47*	-0.101	*-3.54*
1918-1967	D10-D1	0.005	*0.13*	-0.009	*-0.32*	-0.004	*-0.29*	-0.057	*-4.65*
	CAPM's α	0.007	*0.15*	-0.012	*-0.46*	-0.006	*-0.41*	-0.057	*-4.67*
1968-2017	D10-D1	-0.114	*-4.40*	-0.101	*-6.43*	-0.095	*-7.80*	-0.098	*-11.96*
	CAPM's α	-0.110	*-4.28*	-0.101	*-6.39*	-0.094	*-7.74*	-0.098	*-11.92*

Table A.7: Momentum returns of the NYSE data set in different 50-year sub-periods.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1917	D10-D1	0.080	*0.84*	0.048	*0.96*	-0.007	*-0.20*	0.014	*0.53*
	CAPM's α	0.077	*0.81*	0.050	*1.00*	-0.004	*-0.12*	0.018	*0.66*
1918-1967	D10-D1	0.001	*0.03*	-0.008	*-0.37*	0.009	*0.58*	0.021	*1.80*
	CAPM's α	0.004	*0.10*	-0.010	*-0.49*	0.007	*0.46*	0.021	*1.78*
1968-2017	D10-D1	-0.085	*-4.83*	-0.061	*-6.24*	-0.042	*-5.87*	-0.017	*-3.34*
	CAPM's α	-0.084	*-4.78*	-0.062	*-6.25*	-0.042	*-5.85*	-0.017	*-3.40*

Table A.8: Residual momentum returns of the NYSE data set in different 50-year sub-periods.

		Post formation return							
		K=1	*t-value*	K=3	*t-value*	K=6	*t-value*	K=12	*t-value*
-1917	D1-D10	-0.125	*-0.93*	-0.113	*-1.48*	-0.116	*-1.99*	-0.050	*-1.33*
	CAPM's α	-0.121	*-0.90*	-0.107	*-1.40*	-0.111	*-1.91*	-0.049	*-1.32*
1918-1967	D1-D10	-0.091	*-1.76*	-0.095	*-2.94*	-0.091	*-4.02*	-0.060	*-3.78*
	CAPM's α	-0.087	*-1.68*	-0.092	*-2.84*	-0.092	*-4.05*	-0.061	*-3.79*
1968-2017	D1-D10	-0.072	*-2.30*	-0.080	*-4.01*	-0.072	*-4.97*	-0.061	*-6.36*
	CAPM's α	-0.066	*-2.15*	-0.079	*-3.96*	-0.073	*-5.04*	-0.062	*-6.42*

Table A.9: Low volatility of the NYSE data set in different 50-year sub-periods.