Time-series and cross-sectional momentum strategies under alternative implementation strategies

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ABSTRACT

The study compares the performance of alternative implementations of both time-series (Moskowitz et al., 2012) and cross-sectional (Jegadeesh & Titman, 1993) momentum strategies across 24 markets. We find that over our sample period both types of momentum strategies generate positive returns under the majority of implementations evaluated but that time-series momentum is clearly superior. An important difference between the two momentum strategies is that with time-series momentum, the number of stocks included in the winner and loser portfolios vary with the state of the market. As a consequence, cross-sectional momentum digs deeper to select winning stocks when markets are weak and deeper to select losing stocks when markets are strong. As the information in the momentum signals is concentrated in the tails of the return distribution, it is not that surprising that momentum is best implemented using time-series momentum.

Keywords: *Time-series momentum, Cross-sectional momentum, Implementation, Investment performance, Market conditions.*

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1. Introduction

Numerous studies have found that profits that can be realised from following a momentum-based strategy of buying recent outperforming stocks (winners) and selling recent underperforming stocks (losers) (Jegadeesh & Titman, 1993, 2002). The fact that this momentum strategy has proved robust across time, countries and asset classes has led Fama (1998) to observe that momentum remains the "premier unexplained anomaly".[1]

The majority of momentum studies have used cross-sectional momentum as the basis for security selection, choosing stocks on the basis of their ***relative*** performance over some prior period (Jegadeesh & Titman, 1993).[2] In a recent study, Moskowitz et al. (2012) proposed time-series momentum as providing an alternative framework for security selection where securities are chosen on the basis of their ***absolute*** performance over some prior period. Moskowitz et al. (2012) found that time-series momentum performed well both in absolute terms and relative to cross-sectional momentum, across futures markets in equity indices, bonds, currencies and commodities. Baltas and Kosowski (2013) confirmed the strong performance of time-series momentum strategies and highlighted that they drove the performance of many hedge funds. In contrast, Menkhoff et al. (2012) when examining currency markets found that cross-sectional momentum outperformed time-series momentum.

Although previous studies have evaluated the momentum strategy in numerous markets settings, by far the bulk of these studies have concentrated on equity markets. Therefore it is somewhat surprising that we are yet to see a comprehensive study that compares cross-

[1] The momentum strategy has been documented in US stock market (Jegadeesh & Titman, 1993), European stock markets (Bird & Casavecchia, 2006; Rouwenhorst, 1998), emerging stock markets (Hameed & Kusnadi, 2002), international stock markets (Gupta et al., 2010), industries (Moskowitz & Grinblatt, 1999), currencies (Menkhoff et al., 2012) and futures markets (Asness et al., 2013).

[2] The cross-sectional stock selection criteria based on recent returns has been investigated broadly across international stock markets (Rouwenhorst, 1998), industry markets (Moskowitz & Grinblatt, 1999), currency and futures markets (Asness et al., 2013; Menkhoff et al., 2012) as well as the selection criteria on the basis of 52 week high stock prices(George & Hwang, 2004).

sectional and time-series momentum in this arena. The main objective of this study is to redress this deficiency by undertaking a study that evaluates the absolute and relative performance of these two momentum strategies applying multiple implementations across 24 major equity markets[3]. By evaluating multiple implementations, we not only obtain valuable insights into the performance of the two momentum strategies but also how they might best be implemented. Further, we investigate several factors that may give rise to differences in the performance of the two strategies such as differences in the characteristics of the stock selected and the performance of the strategies under different markets conditions.

We find that time-series momentum generates profits for the majority of the implementations evaluated in all 24 markets and that that these profits are significant in the vast majority of instances. Cross-sectional momentum also proves to be a highly profitable strategy although a comparison of the performance of the two momentum strategies that time-series momentum is superior particularly under the better implementations. We confirm that both momentum strategies perform best in up markets and that the superiority of time-series momentum is largely due to its excellent performance in such markets. Indeed, we find that a most likely explanation for the better performance of time-series momentum is that it is a consequence of the approach to stock selection embedded in time-series momentum being more in tune with market conditions. Two of the more interesting markets evaluated in our study are Japan and the US. Although confirming that cross-sectional momentum is not a good investment strategy to pursue in Japan, we find that the same is not true for time-series momentum which would seem to offer profitable opportunities under the majority of implementations. Overall we find that neither form of momentum performs particularly well in the US market over our

[3] The countries examined included the 23 countries included in the MSCI World Index (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK and the US) plus Greece.

sample period. Digging deeper, we find that this is due to their performance in the US being much worse during the GFC than was the case for the other markets.

The remainder of the study is organised as follows. In Section 2, we compare the cross-sectional and time-series momentum strategies. Section 3 and 4 discuss the data and the various implementations of the momentum trading strategies. In Section 5, we analyse the results of both momentum strategies while Section 6 provides us with the opportunity of to summarise our findings.

2. Cross-sectional versus time-series momentum

Cross sectional and time-series momentum both select stocks on the basis of their performance over some prior (formation) period. The only difference between the two approaches being that cross sectional momentum assigns stocks to the winner and loser portfolio on the basis of their ***relative*** performance while time-series momentum assigns stocks on the basis of their ***absolute*** performance. With cross-sectional momentum, all stocks are ranked on the basis of their performance over the formation period with the best performing stocks (e.g. top 20%) being assigned to the winner portfolio and the worst performing stocks (e.g. bottom 20%) being assigned to the loser portfolio. With time-series momentum, stocks that realised a return over the formation period above a certain level (e.g. +5%) are assigned to the winner portfolio and those that realise a return below a certain level (e.g. -3%) are assigned to the loser portfolio. In both cases, the profitability of the strategy is measured by the aggregate of the return from of a zero-investment strategy of taking a long position in the winner portfolio and a short position in the loser portfolio.

Given that both strategies identify winner and loser stocks based on their past performance, at any point in time they will hold many stocks in common. However more importantly, the different stock selection rules embedded in each of the momentum strategies will ensure that that there will be differences in their holdings. As we will demonstrate, time-series momentum will assign more stocks to the winner than to the loser portfolio when markets are strong, with the opposite being the case during periods when markets have been experiencing weak performance. In contrast, cross sectional momentum will always assign the same number of stocks to each portfolio irrespective of how the market is performing. Hence there is a timing element in the selection of stocks embedded in time-series momentum which does not exist in cross sectional momentum. An interesting question to ask is whether this key difference between the two strategies translates into any significant difference in performance (and why), especially in the light of the findings of Cooper et al. (2004) that show the performance of cross sectional analysis is conditioned by the performance of the market.

A major contribution of this paper is to provide evidence on the relative and absolute performance of cross sectional and time-series momentum across 24 developed markets utilising numerous implementations. In particular by comparing "like-for-like" across 768 implementations and 24 markets, we will provide the most comprehensive evidence to date as to which of cross sectional and time-series momentum realises the best investment outcomes in equity markets and insights into why the performance of the two strategies differ. In addition, we provide important insights into the absolute performance of each of the momentum strategies during a period when markets experienced both rapid growth and rapid decline and thus encompass conditions when momentum should both thrive and struggle.

Jegadeesch and Titman (1993) was the first academic paper to highlight the profitability of momentum as an investment strategy when they examined the performance of equally weighted portfolios of stocks chosen on the basis of their performance over several combinations of formation periods and held for several holding periods. They found evidence that the stocks with best past performance (top 10%) outperformed those stocks with the worst past performance (bottom 10%) although the extent of this outperformance was very much a function of how the strategy was implemented. They concluded that these anomalous findings could not be explained by risk factors and suggested the need for a more "sophisticated model of investor behaviour". Rouwenhorst (1998) conducted the first international study of momentum and found that it delivered outperformance in 11 out of 12 European markets. Rouwenhorst (1999) subsequently extended this study to 20 emerging markets with similar (albeit slightly weaker) findings. Jegadeesch and Titman (2001) re-examined the momentum strategy over a longer time period and found little evidence of any deterioration in its performance. They also noted at the time that the available evidenced supported the persistence of the performance of the over relatively long periods and across all of the developed markets, with the exception of Japan (Asness, 2011; Hanauer, 2014). The more recent evidence is still strongly supportive of the continuation of the momentum anomaly although there is some suggestion that it might be waning in the US market (Hwang and Rubesam, 2013). The Australian evidence is largely supportive of the momentum strategy performing well in this market with Gaunt and Gay (2003), Haun and Pavlov (2003), and Demir et al. (2006) all finding momentum profits ranging between 5%pa and 16%pa. However, there is some counterevidence with both Durand et al. (2006) and Brailsford et al. (2012) failing to identify any significant momentum profits.

The pervasiveness of the empirical findings on momentum has stimulated numerous studies seeking an explanation for its apparent continued profitability. These studies can broadly be split into two camps. One group that proposes more traditional explanations aimed at establishing that the findings are due to methodological flaws in the research design (e.g. failure to control for risk, transaction costs). A second group who argue that the momentum profits are attributable to irrational behaviour of investors that results in stocks prices both under- and over-reacting to information signals. As the focus of this paper is not on providing explanations for past findings, we will not go further with this debate other than to observe that the success of a momentum investment strategy is dependent on stocks trending for a sustained period in both directions.

3. Data

The sample covers the 24 major stock markets mentioned previously. The period covered extends from 1990 to 2012 and covers both bull and bear markets. The daily and monthly returns and the market value for all active and dead stocks were obtained from Thomson Reuters DataStream[4]. Following Ince and Porter (2006), we apply several screening procedures to our sample stocks. For a stock to be included in our analysis in a particular month, it must have both return and market capitalization data available. In accordance with Chui et al., (2010), monthly returns will be trimmed if the market capitalization of a stock is below the bottom fifth percentile of all stocks within a given country in any month. Following McLean et al. (2009), we winsorise daily and monthly returns within a given country at the top and bottom 1% to minimise the effects of outliers.

Table 1: Summary Statistics

This table reports for each market the total number of stocks, the average number of stocks each month, the average monthly returns of a portfolio consisting of all stocks in our universe based on equal weight (EW), market weight (MW) and inversed-volatility weight (INVSTD) calculated over various periods, the average monthly market value and monthly book-to-market value. We leave out the first two year as preparation for the momentum strategies and therefore all results in this paper are from 1992 to 2012

[4] We also conducted the analysis for the U.S. market using CRSP data and obtained substantially the same results.

Country	Sample Size		Average Monthly Return (%)						Average monthly market value (local currency)	Average monthly book-to-market
	No. of stocks	Average monthly	EW	MW	IVOL3	IVOL6	IVOL9	IVOL12		
Australia	2,880	1,141	1.53	1.14	0.82	0.88	0.91	0.91	795.16	0.74
Austria	218	96	0.43	1.14	0.31	0.28	0.31	0.32	771.28	1.48
Belgium	335	157	0.63	1.17	0.61	0.62	0.60	0.63	1,581.74	1.24
Canada	3020	1,200	1.69	1.81	0.72	0.81	0.82	0.81	874.93	0.88
Denmark	360	195	0.59	1.55	0.57	0.57	0.60	0.59	3,509.55	0.90
Finland	213	106	1.19	1.85	1.10	1.14	1.17	1.19	1.049.72	0.73
France	1,991	828	0.96	1.43	0.47	0.41	0.51	0.56	1,365.10	0.81
Germany	1,450	663	0.47	1.33	0.28	0.34	0.31	0.35	1,182.44	1.71
Greece	415	224	1.07	1.39	0.91	0.82	0.93	0.94	2,205.63	1.03
Hong Kong	1,404	715	1.38	1.98	1.02	1.23	1.28	1.41	7,220.63	1.41
Ireland	131	58	1.02	1.61	1.02	0.88	0.80	0.80	827.88	0.92
Israel	843	475	1.19	1.67	0.93	0.91	0.89	0.87	1,443.25	1.14
Italy	543	241	0.33	1.35	0.27	0.35	0.37	0.38	53,971.55	0.91
Japan	2,990	2.096	0.27	0.71	0.03	0.12	0.16	0.18	168,479.61	0.99
Netherlands	304	160	0.72	1.33	0.73	0.77	0.80	0.82	2,609.86	0.96
New Zealand	279	115	1.05	1.47	1.55	1.00	0.97	0.98	386.18	0.84
Norway	479	165	1.22	1.91	1.05	1.06	1.04	1.06	4,335.38	0.95
Portugal	198	92	0.78	1.26	0.83	0.69	0.54	0.56	1,181.20	1.30
Singapore	792	367	1.10	1.36	0.93	0.91	0.98	0.96	1,206.81	1.06
Spain	281	145	0.71	1.06	0.63	0.69	0.66	0.71	4,280.14	0.80
Sweden	906	308	1.15	1.92	1.04	1.12	1.17	1.18	5,979.49	0.92
Switzerland	412	235	0.79	1.19	0.80	0.77	0.77	0.79	3,534.89	1.24
UK	4,212	1,601	0.66	1.39	0.24	0.43	0..49	0.61	814.17	0.73
US	10,041	4,232	1.52	1.65	1.05	0.99	1.03	1.02	2,671.34	0.62

The first two columns of Table 1 display the total number of stocks, and the average number of stocks per month, included for each of our 24 markets. The total number of stocks aggregated to 34,697 across 24 developed markets with the U.S. market having the largest number of stocks with 10,041 stocks and Ireland having the smallest number with 131 stocks. We also report the average monthly returns of a portfolio consisting of all stocks available each month weighted using one of several weighting schemes: equal weights (EW), market value weights (MW) and four sets of returns for inverse volatility weights (IVOL) depending on the period over which volatility is measured. Finally, we report the average market value and book-to market ratio across all of the stocks in each of the 24 markets. These numbers will provide a useful reference when examining the characteristics of the winner and loser portfolios in each country.

4. Momentum Implementation Strategies

The success of the momentum strategies depends on stocks trending for sustained periods in both directions. This is best articulated in the momentum life cycle of Lee and Swaminathan (2000) which suggests that stock prices typically oscillate around their fair value. In such a world, the success of any momentum strategy will depend on it being based on implementation rules that are in harmony with the periodicity of the (mis)pricing cycles. As momentum trading signals are based on recent pricing movements, they will always be late in identifying winning and losing securities. However, the more successful momentum strategies will be those based on implementation rules that results in identifying winners (losers) early in their up-(down) cycle and reversing these positions in (close to) an optimum fashion.

There are very limited insights that we get from theory as to what implementation rules will produce the best outcomes, leaving it largely as an empirical question. In this paper we provide comprehensive evidence on the absolute and relative performance of time-series and cross-sectional momentum under (almost) all of the implementation rules that have been used in previous studies and in so doing show how sensitive this performance is to the implementations chosen and also provide insights into what might be the optimum implementations. The various implementation rules are discussed below in terms of the contribution that they make to the two components of the investment process: stock selection and portfolio construction.

4.1. Stock Selection

Stock selection involves identifying the stocks in which to take both long and short positions invest or short. For both momentum strategies, stock selection has the following components:

4.1.1. Specifying the prior period over which to measure stock returns (the formation period):

The importance of this decision is to set the formation period long enough to identify the establishment of true trends in markets but not too long so as to leave the identification of the trend until too late in the cycle. In this study we examine four formation periods (J) of three, six, nine and 12 months.

4.1.2. Specifying the cut-off rule that identifies stocks as being either winners or losers:

With cross-sectional momentum, this involves ranking stocks on the basis of their performance over the previous J months and then identifying as winners those stocks that rank in the top x% of the distribution, and as losers those stocks that rank in the bottom x%. One value for x that we examined in this study was 50% which results in all stocks being designated as either winners or losers. The use of this cut-off would suggest that past performance provides a good signal of future performance across the whole range of performance outcomes. Dating back to the original study of Jegadeesh and Titman (1993), the strength of the information signal has been shown to degrade as one proceeds down the rankings. In order to demonstrate this, we also examine the situation where we set the cut-off at 30% and 16%.

With time-series momentum, the cut-off for identifying winners and losers is an absolute number(s). Moskowitz et al. (2012) used a method where all stocks that realise a positive past return were identified as winners and those that realise a negative return were identified as losers. Another similar method that we use with time-series momentum is to set the cut-off as the market return over the formation period. Of course, each of these rules results in every stock in the investment universe being classified as either a winner or a loser. In order to match the situation where the cut-offs under cross-sectional momentum are set at 30% (16%), we set symmetric upper and lower cut-offs for time-series momentum which result on average in 60% (32%) of the investment universe being classified as either a winner or a loser when measured across the whole sample period.[5]

4.2. Portfolio Construction

The portfolio construction decisions involve determining at the time of each rebalancing, the proportion of the portfolio (weights) that are allocated to the winning stocks and the losing stocks in their respective portfolios. There are three separate decisions that in combination determine these weights:

4.2.1. The holding period

This is a rule common to both momentum strategies that determines the period that a particular stock is held once it is included in either the winner or the loser portfolio. For example, if the holding period is six months, then a stock acquisition will be reversed six months after the stock has been acquired. As mentioned earlier, the implementation rules have to be in harmony with the periodicity of the oscillations of the typical stock. In other words, the aggregate of the formation and holding periods should approximate the period of the upward and downward cycles for the typical stock. In this study we examine holding periods (H) of three, six, nine and 12 months.

[5] The cut-offs were chosen because they equate with cut-offs which are determined as being 0.5 (1.0) standard deviations from the mean in order over the same to allocate 60% (32%) of the stocks either the winner or loser portfolios

4.2.2. The period for portfolio rebalancing:

One portfolio rebalancing strategy that we examine is a buy and hold strategy where the portfolio is rebalanced at the end of each holding period (BHAR). For example, if the holding period is six months then the portfolio is rebalanced every six months with the portfolio acquired six months ago being sold and replaced by a new portfolio. The alternative we consider is that the portfolio is rebalanced every month irrespective of the holding period for the stocks (CAR). Again assume a holding period of six months which means that with monthly rebalancing, the portfolio holdings acquired six months will be replaced with new holdings which means that approximately one-sixth of the portfolio will be turned over each month. Jegadeesh and Titman (1993) considered these two strategies for rebalancing and found monthly rebalancing to be superior.

A further matter to take into account is the role that the bid-ask spread takes in explaining momentum. It is quite possible that stocks that have performed well (poorly) over some prior period are near the top (bottom) of the bid-ask spread. This being the case, particularly short-term future performance may be eroded by pricing moving back towards the midpoint of the bid-ask spread. This raises the possibility that better performance might be realised by delaying trading for a short time after a stock has been identified as a winner or a loser. In this study we also look at buy-and-hold strategies and monthly rebalancing where trading is delayed by one month. This means that in total we consider four rebalancing strategies: BHAR (0), BHAR (1), CAR (0) and CAR (1).

4.2.3. The determination of the weights assigned to stocks:

Once it is determined what assets to include in a portfolio, it is then necessary to allocate portions of the total funds available in specific stocks. The two most common methods evaluated in the academic literature are to equally weight each stock (EW) or to apportion funds to stocks based on the market weight of the stock's equity (MW). An important difference between these two methods being that by equally weighting the portfolio holdings are more skewed towards stock in smaller companies. A third method of weighting stocks used in this study is to base the proportion of funds allocated to each stock on the inverse of the volatility of the returns of the stocks to be included in each portfolio (I-VOL)[6]. This is similar to the method employed in Moskowitz et al. (2012) and tilts the portfolios towards stocks with lower volatility and so produces investment portfolios with lower risk.

A summary of the 768 implementations that are examined for each of cross-sectional and time-series momentum implementation strategies to be examined is set out in Table 2.

Table 2. Implementation Options for Time-Series and Cross-Sectional Momentum

<table>
<tr><td rowspan="4">Stock selection</td><td colspan="2">Stock selection criteria</td><td>Cross-sectional momentum</td><td>Time-series momentum</td></tr>
<tr><td colspan="2">Formation periods</td><td colspan="2">J = 3, 6, 9 and 12 months</td></tr>
<tr><td rowspan="2">Cut-off Point</td><td>Invest in whole sample</td><td>Winner/Loser portfolio contains top/bottom 50% stocks in the entire market</td><td>The absolute cut off point for winner and loser portfolios is a 0% return (or alternatively, the market return for the period)</td></tr>
<tr><td>Invest in 32% (60%) of sample</td><td>Winner/Loser portfolio contains top/bottom 16% (30%) of stocks in the entire market</td><td>Absolute cut off points of winner (loser) portfolios are calculated as the average monthly return on all stocks over the entire sample period plus/minus approximately one (half) standard deviation.</td></tr>
<tr><td rowspan="3">Portfolio Construction</td><td colspan="2">Rebalancing regime[7]</td><td colspan="2">CAR(0) and CAR(1)
BHAR(0) and BHAR(1)</td></tr>
<tr><td colspan="2">Portfolio weights</td><td colspan="2">Equal weight (EW)
Market value weight (MW)
Inversed-volatility weight (I-VOL)</td></tr>
<tr><td colspan="2">Holding periods</td><td colspan="2">H = 3, 6, 9 and 12 months</td></tr>
</table>

[6] The volatilities are estimated using daily returns over the formation period used in the particular implementation.

[7] To be consistent with Fama (1998), BHAR indicates momentum return has been calculated by buy-and hold construction and CAR indicates momentum return has been calculated by monthly rebalancing construction. BHAR (0)/BARH (1) present BHAR with zero/1 month gap between formation and holding periods.

5. The Results

Table 3 reports the average monthly returns for 16 (J x H) time-series momentum strategies across the 24 markets along with an indication of whether the returns are significant at the 1% (1), 5% (5) and 10% (10) levels[8]. The specific strategy being to form a long portfolio consisting of the identified winning stocks and a short portfolio consisting of the identified losing stocks with the average monthly returns reported being the aggregate of the monthly returns on the two portfolios. The reported results all relate to the implementation where the cut-offs for selecting the stocks to be included in the cross-sectional momentum portfolios are set at 16%.[9] There were 192 implementations evaluated for each time-series and cross-sectional momentum but we report only on the returns on what we call the "best", "median" and "worst" implementations.[10] In order to identify these three sets of results we aggregate the monthly returns for the time-series and cross- sectional momentum for each of the implementations, rank them and then choose the best (highest ranking), the median (middle ranking) and the worst (lowest ranking). A consideration of the results for these implementations provides useful insights into the absolute and relative performance of the two momentum strategies, how this profitability is conditioned by the implementation used, and so what implementation strategies are best to apply.

[8] Newey-West t-statistics were calculated in order to determine the significance of the average monthly returns.

[9] In order to determine the cut-offs for time-series momentum for each market, we calculated the mean and standard deviation of the returns for all stocks across the total sample period in each market and set the cut-offs at one standard deviation above, and one-standard deviation below, the mean. For example, the cut-offs set for Australia were +5.99%% for the winner stocks and -4.14%% for the loser stocks. This is an effective "in-sample" means of calculating the cut-offs as they are based on the mean and standard deviations of the returns of the stocks in our universe over the entire sample period. We also determined and applied cut-offs determined "out-of-sample" by setting new cut-offs each calendar year based on the history of stock returns realised in past period. When applying these "out-of-sample" cut-offs, we obtained results almost identical to those reported in this paper

[10] Simply presenting the tables for the performance of all the implementations considered would take 36 pages so we have chosen to encapsulate the insights provided across all the implementations by largely restricting our reporting to these three implementations.

Table 3: Momentum Performance under Best, Median and Worst Implementation

This table reports the average monthly returns of losers (L), winners (W), momentum (W-L) portfolios for time-series (TSM) and cross-sectional (CSM) momentum strategies and the return difference between TSM and CSM for the best, median and worst implementation in each of the markets. These implementations are determined by adding the average monthly returns of the two momentum strategies under each of the implementations, ranking them and the identifying the best, median and worst.

Market	Implementation				Time-series (%)			Cross-sectional (%)			TSM –
		JxH	Weight	Construction	W	L	W- L	W	L	W - L	CSM (%)
Australia	Best	9x3	MW	BHAR(0)	2.75^{1}	-0.01	2.76^{1}	2.04^{1}	0.18	1.86^{1}	0.90^{10}
	Median	12x6	IVOL	CAR(1)	1.31^{1}	0.57	0.74^{1}	1.14^{5}	0.52	0.62^{10}	0.12
	Worst	12x9	EW	BHAR(1)	0.98^{10}	1.38^{5}	-0.40	0.92^{10}	1.17^{5}	-0.25	-0.15
Austria	Best	12x3	IVOL	CAR(0)	1.21^{1}	-0.36	1.57^{1}	1.14^{1}	-0.26	1.40^{1}	0.18
	Median	12x3	MW	CAR(0)	0.86^{5}	-0.16	1.01^{10}	1.04^{1}	0.27	0.76	0.25
	Worst	12x12	MW	BHAR(1)	-0.05	0.53	-0.57	0.70^{10}	0.59	0.11	-0.68
Belgium	Best	12x3	IVOL	CAR(1)	1.19^{1}	-0.60	1.79^{1}	1.37^{1}	-0.28	1.63^{1}	0.16
	Median	12X9	EW	BHAR(1)	0.76^{1}	-0.20	0.97^{1}	1.00^{1}	-0.16	1.17^{1}	-0.20
	Worst	3x9	MW	BHAR(0)	0.33	0.36	-0.03	.036	0.85^{10}	-0.49	0.46
Canada	Best	9x3	MW	BHAR(0)	3.04^{1}	-0.08	3.13^{1}	2.37^{1}	0.31	2.06^{1}	1.07^{1}
	Median	9x6	EW	CAR(1)	2.17^{1}	0.94	1.23^{1}	2.10^{1}	1.09^{10}	1.02^{1}	0.21
	Worst	12x12	EW	CAR(1)	1.72^{1}	1.48^{1}	0.24	1.55^{1}	1.63^{1}	-0.08	0.32^{5}
Denmark	Best	9x3	IVOL	BHAR(1)	1.30^{1}	-0.75	2.05^{1}	1.21^{1}	-0.53	1.74^{1}	0.31
	Median	12x9	MW	CAR(1)	1.43^{1}	0.04	1.39^{1}	1.25^{1}	0.04	1.20^{1}	0.18
	Worst	3x9	MW	BHAR(1)	0.78^{10}	0.58	0.19	1.15^{1}	0.48	0.67	-0.48
Finland	Best	12x6	MW	BHAR(0)	3.00^{1}	0.01	2.98^{1}	1.95^{1}	0.24	1.72^{5}	1.26^{10}
	Median	12x6	IVOL	CAR(0)	1.77^{1}	0.50	1.27^{5}	1.55^{1}	0.66	0.89^{5}	0.38
	Worst	3x6	EW	BHAR(0)	0.67	0.83	-0.10	0.99^{5}	0.71	0.29	-0.39
France	Best	3x12	IVOL	CAR(1)	1.34^{1}	0.09	1.43^{1}	1.26^{1}	0.15	1.11^{1}	0.33^{5}
	Median	3x9	IVOL	BHAR(0)	0.94^{1}	0.36	0.58^{10}	1.03^{1}	0.52	0.51	0.06
	Worst	3x3	MW	BHAR(0)	0.83^{5}	1.36^{5}	-0.53	0.49	1.10^{10}	-0.61	0.09
Germany	Best	12x3	IVOL	CAR(0)	1.05^{1}	-0.79	1.85^{1}	1.09^{1}	-0.53	1.62^{1}	0.23
	Median	12x3	NW	BHAR(1)	1.36^{1}	0.00	1.35^{1}	1.31^{1}	0.38	0.92	0.43
	Worst	3x12	IVOL	BHAR(0)	0.58^{10}	0.20	0.38	0.21	0.66	-0.45	0.84
Greece	Best	3x12	MW	BHAR(1)	1.31	-0.47	1.78^{5}	1.70^{10}	0.30	1.38	0.40
	Median	6x9	IVOL	CAR(1)	0.71	0.36	0.35	0.97	0.66	0.31	0.04
	Worst	12x12	EW	BHAR(1)	0.04	1.08	-0.93	0.41	1.32	-0.91	-0.02
Hong Kong	Best	6x3	MW	BHAR(0)	2.37^{1}	0.16	2.21^{1}	1.81^{1}	0.47	1.34^{1}	0.87^{10}
	Median	12x6	IVOL	BHAR(0)	1.39^{1}	0.71	0.70	0.92	0.96	-0.04	0.74^{10}
	Worst	12x12	EW	BHAR(1)	0.78	1.46^{10}	-0.61	0.67	1.40^{10}	-0.73^{5}	0.12
Ireland	Best	6x12	MW	BHAR(0)	2.26^{1}	-1.32	3.58^{1}	2.07^{1}	-0.29	2.36^{5}	1.22^{5}
	Median	6x3	IVOL	CAR(1)	1.00^{5}	0.58	0.42	1.29^{1}	0.38	0.91^{10}	-0.48
	Worst	3x9	MW	BHAR(1)	0.03	1.42	-1.38	0.40	1.74^{5}	-1.34	-0.03
Israel	Best	9x12	MW	BHAR(0)	2.04	0.02	2.02^{1}	1.70	0.05	1.66^{1}	0.36
	Median	6x6	IVOL	CAR(1)	1.02^{5}	0.93	0.10	1.21^{5}	0.95	0.26	-0.16
	Worst	3x12	EW	BHAR(0)	0.82	1.38^{5}	-0.56	0.79	1.25^{5}	-0.46^{10}	-0.10
Italy	Best	12x6	MW	BHAR(0)	1.16^{10}	-1.10^{5}	2.26^{1}	1.34^{5}	-0.04	1.38^{1}	0.88
	Median	9x3	MW	CAR(0)	1.18^{1}	-0.24	1.42^{1}	1.16^{5}	0.29	0.87^{10}	0.55
	Worst	3x6	MW	BHAR(0)	0.29	.034	-0.05	0.60	0.23	0.37	-0.42
Japan	Best	3x12	MW	BHAR(0)	0.38	-0.71	1.09^{1}	0.31	0.06	0.24	0.84^{1}
	Median	9x3	IVOL	BHAR(1)	0.21	-0.15	0.37	0.03	0.23	-0.20	0.56^{1}
	Worst	12x12	EW	BHAR(1)	0.00	0.09	-0.09	-0.11	0.3	-0.47	0.38^{5}

Market	Implementation				Time-series (%)			Cross-sectional (%)			TSM – CSM (%)
		JxH	Weight	Construction	W	L	W- L	W	L	W - L	
Nether-lands	Best	9x3	EW	BHAR(0)	1.42^{1}	-0.99^{10}	2.40^{1}	1.26^{1}	-0.32	1.58^{1}	0.81^{5}
	Median	6x12	EW	BHAR(0)	1.11^{5}	-0.36	1.47^{1}	0.87^{5}	-0.02	0.89^{1}	0.58
	Worst	12x12	MW	BHAR(1)	0.18	0.42	-0.25	0.63	0.60	0.04	-0.28
New Zealand	Best	9x3	IVOL	BHAR(0)	2.67^{1}	-0.18	2.82^{1}	1.72^{1}	-0.01	1.73^{1}	1.09^{10}
	Median	6x12	IVOL	CAR(0)	1.65^{1}	0.29	1.36^{1}	1.41^{1}	0.26	1.15^{1}	0.21
	Worst	3x12	MW	BHAR(1)	0.89^{5}	1.09^{10}	-0.20	0.82^{5}	0.42	0.40	-0.60
Norway	Best	9x3	IVOL	BHAR(0)	2.29^{1}	0.22	2.07^{1}	1.98^{1}	0.41	1.57^{1}	0.50
	Median	12x9	IVOL	BHAR(1)	1.36^{5}	0.39	0.97^{10}	1.54^{1}	0.76	0.78^{10}	0.19
	Worst	3x3	MW	BHAR(0)	2.09^{1}	2.02^{5}	0.08	1.52^{5}	1.40^{5}	0.12	-0.05
Portugal	Best	6x6	MW	BHAR(1)	1.50^{5}	-0.60	2.08^{5}	0.40	-0.49	0.89	1.19^{10}
	Median	12x3	MW	CAR(0)	0.91^{10}	0.57	0.35	0.85	0.27	0.58	-0.23
	Worst	3x3	EW	CAR(0)	0.66	1.54^{1}	-0.88^{10}	0.72^{10}	1.35^{1}	-0.63^{10}	-0.25
Singapore	Best	9x3	IVOL	BHAR(0)	1.46^{5}	-0.19	1.64^{1}	1.34^{1}	0.47	0.87^{10}	0.77^{5}
	Median	12x9	IVOL	BHAR(1)	1.45^{5}	0.22	1.25^{5}	0.88	0.85	0.04	1.22^{5}
	Worst	9x12	MW	BHAR(1)	0.67	1.13	-0.41	0.63	1.05	-0.42	0.01
Spain	Best	12x6	EW	BHAR(0)	1.48^{1}	0.05	1.42^{1}	1.11^{1}	0.11	1.00^{1}	0.42
	Median	12x9	IVOL	BHAR(1)	0.67	0.49	0.18	1.24^{1}	0.20	1.04^{1}	-0.86^{10}
	Worst	3x6	MW	BHAR(0)	-0.08	1.21^{10}	-1.28^{10}	0.15	0.93^{10}	-0.79	-0.49
Sweden	Best	12x3	IVOL	BHAR(1)	2.02^{1}	-0.81	2.81^{1}	1.64^{1}	0.27	1.37^{1}	1.44^{1}
	Median	6x12	IVOL	CAR(0)	1.51^{1}	0.16	1.35^{1}	1.441	0.52	0.92^{1}	0.43^{10}
	Worst	3x12	MW	BHAR(0)	1.07^{10}	0.77	0.30	0.91	1.37^{5}	-0.46	0.80
Switzer-land	Best	12x3	IVOL	CAR(0)	1.69^{1}	-0.09	1.75^{1}	1.45^{1}	0.14	1.32^{1}	0.44
	Median	6x9	EW	BHAR(0)	1.17^{1}	0.21	0.95^{1}	1.17^{1}	0.36	0.81^{5}	0.13
	Worst	3x3	MW	BHAR(0)	0.57	0.52	0.05	0.86^{5}	0.77^{10}	0.09	-0.04
UK	Best	12x3	IVOL	CAR(0)	1.61^{1}	-0.54	2.15^{1}	1.52^{1}	-0.33	1.85^{1}	0.30^{10}
	Median	6x9	IVOL	BHAR(0)	1.15^{1}	-0.04	1.20^{1}	1.07^{1}	0.03	1.04^{1}	0.16
	Worst	3x3	MW	BHAR(0)	1.12^{1}	0.81	0.31	0.93^{5}	1.02^{10}	-0.10	0.40
US	Best	9x3	MW	CAR(1)	1.70^{1}	0.89^{5}	0.87^{5}	1.72^{1}	1.07^{5}	0.64	0.23
	Median	3x12	MW	BHAR(1)	1.24^{5}	0.90^{5}	0.34	1.34^{1}	1.16^{1}	0.18	0.16
	Worst	12x12	EW	BHAR(1)	1.35^{1}	1.62^{1}	-0.26	1.31^{1}	1.77^{1}	-0.46	0.20

5.1. The profitability of the momentum strategies:

<u>Time-series momentum</u>

There is clear evidence that time-series momentum has realised excellent performance across the majority of our 24 markets under the best implementation. We find that this strategy yields positive and significant returns in all 24 markets with the average monthly return across these markets being in excess of 2% per month which represents an annualised return of in excess of 28%. Of course, not everyone would choose to use what proves to be the optimum implementation so it is appropriate to examine how time-series momentum would perform under an “average” implementation. Under the median implementation, all markets continue to yield a positive performance with the average annualised return across the 24 markets being in excess of 11%. Despite a falloff in performance as we move from the best to the median implementation, it proves that time-series momentum still yields significant positive returns in 16 of the 24 markets. Not surprisingly, we see further degradation in the performance of time-series momentum when we come to look at the worst implementation. Now the strategy only yields positive performance in seven markets with the average monthly return across all markets being -0.25%. What the above discussion highlights is that time-series momentum is a profitable strategy across all of the markets for the majority of implementations. However, it also highlights the sensitivity of the performance to the implementation chosen.

Cross-sectional momentum

Cross-sectional momentum has the runs on the board with so many studies across numerous markets and time periods finding it to be the source of a profitable investments strategy. In general, we find evidence to support this prior evidence with the best implemented strategy yielding positive returns in all 24 countries. The positive returns only prove to be significant in 20 of the markets and the average monthly return across all markets is slightly less that 1.5% which yields an annualised return of around 18.5%. When combined with a median implementation, cross-section momentum realises a positive return in all but Hong Kong and Japan. These positive returns are significant in 14 of these markets and average approximately 8.5% per annum. This degradation in performance continues and we move to the worst implementation with positive returns now only being realised in eight of the 24 markets. Indeed, the worst implementation of the cross-sectional momentum strategies produces three markets where there are significant negative returns as compared with no markets with significant positive returns. In general our findings confirm that cross-sectional momentum provides the basis for a good investment strategy in the majority of markets but also emphasise that the extent of the profits that can be generated is very much dependent upon the implementation strategy used. Our findings confirm that cross-sectional momentum does not yield significant profits in Japan under any of our numerous implementations. We also find that there is not a single implementation that yields a significant positive return in the US market which provides support to the proposition put forward by Hwang and Rubesam (2013) that cross-sectional momentum is waning in that market.

Time-series v cross-sectional momentum

A major focus of this paper is the relative performance of time-series and cross-sectional momentum. In the last column of Table 3, we present the difference between the returns on these two strategies and find that under the best implementation that time-series momentum outperforms cross-sectional momentum in all 24 markets. This outperformance is significant in 13 of the markets and the average difference across all markets is slightly less than 0.7% per month or an annualised 8.2%. It is clear that with optimum implementation time-series momentum is the superior of the two momentum strategies over our sample period. When we move to the median implementations, we find that time-series momentum continues to generate the highest return in all markets except Belgium, Ireland, Israel, Portugal, and Spain. However, the outperformance in many countries is minimal, averaging only 0.24% per month across the 24 markets and only being significant in four markets. The relative performance of time-series momentum erodes ever further when we consider the worst implementation. Now it is superior in only nine markets, none of which are significant with the difference between the returns on the two momentum strategies across the 24 markets being approximately zero.

The general conclusion that we draw from our findings is that with the best implementation, there is no doubt that the time-series approach provides a better basis on which to build a momentum strategy. This advantage definitely erodes as one moves to less optimal implementations but it still remains the preferable approach in the majority of markets for the majority of implementations. Before moving on to examine more closely some of the implementation issues, it is interesting to reflect on our findings for the Japanese markets. Previous findings using cross sectional momentum have consistently found that momentum is not a profitable strategy in Japan. We confirm these findings with cross sectional momentum yielding negative returns under the majority of the implementations examined. However, we also find that Japan is the only market where time-series momentum yields a significant higher return relative to cross-sectional momentum under the best, median and worst implementations. Our findings suggest that time-series momentum offers more potential to Japanese investors with it yielding almost 1.1% per month under the best implementation.

5.2. The Alternative Implementations

There are four key matters (ignoring for the present the cut-offs) that have to be addressed when determining the implementation policy: the formation period, the holding period, the rebalancing regime and the weighting scheme. Our analysis has told us that it barely matters what rebalancing scheme is used so in our discussion we shall concentrate on the other three:

The Formation Period

The purpose of the formation period is to allow sufficient time to identify trending stocks with a balance to be made between setting the period too short and so acting on a number of false signals and setting the period too long that "too much money is left on the table". We find that the best implementation typically involves a relatively long formation period of either nine or 12 months, with this being the case in 16 of the 24 markets. In contrast the worst strategy involves a formation period of three months in 15 of the 24 markets.

The Holding Period

The optimal holding period will very much depend upon the length of the typical pricing cycle for a stock and the formation period being used. In the case of our best implementation, a holding period of three month is used in 15 of the 24 markets. As one proceeds to inferior implementations, the holding periods gradually lengthens (as the formation period gradually reduces). In the case of the worst implementation, half of the markets now use a formation period of 12 months. As we intimated earlier, the key to a successful momentum strategy is an implementation that is in harmony with the periodicity of the typical stock. Our analysis would suggest a periodicity (i.e. low to high and high to low, both relative to the market) is approximately 15 months.

The Weighting Scheme

We considered three weighting schemes: equal weights, market weights and weights based on each stock's volatility. The major insight to be obtained from the best implementations is that they steer well away from using equal weights with this only being used in two markets with the other markets being equally split between the two other weighting schemes. When we move to the worst implementation, the major change is that there is only one market that involves an IVol weighting scheme. To a large extent, the best weighting scheme will be dependent the characteristics of the stocks that perform well over the sample period. For example, the relatively poor performance of equal weighting is largely due to the underperformance of small caps while the good performance of inverse volatility reflects that low risk/quality stocks did relatively well over our sample period.

Summary

We found that the best single implementation if it was applied across all 24 markets is to combine a 12 month formation period with a three-month holding period, to use inverse volatility to weight the stocks and to rebalance the portfolios monthly with no lag in implementation. This is consistent with the findings discussed above for individual markets that suggested that the highest returns would be achieved when implementing the momentum strategies by combining a long formation period with a short holding. It is also in line with previous discussion that suggesting inverse-volatility based weights ranked highly across markets as the best way of assigning weights to stocks. The single worst implementation strategy (for the 24 markets) differs in that it has a combined formation and holding periods each of 12 months, and involves equal weighting and a buy-and-hold strategy with a one-month lag. The most deleterious feature being the combined 24 months that is well beyond the periodicity of the typical stock and so involves buying high and selling low.

5.3. *Cut-off Points*

All of the analysis to date has been on the basis of cut-offs designed to assign 32% of available stocks to either the winner of loser portfolio. In order to investigate the sensitivity of the momentum profits to the cut-off used, we also evaluated the implications of cut-offs that involved allocating both 60% and 100% of the stocks to the winner and loser portfolios.

We provide summary results in Table 4 on the absolute and relative performance of the two momentum strategies based on the best, median and worst implementations for each market based on four definite cut-offs[11]. A review of this information highlights the exceptional performance of both momentum strategies perform but that their performance degrades as the cut-off points are relaxed to include more stocks into the portfolios. For example with

[11] Detailed results for each of the 24 countries is available in an on-line Appendix

median implementation, time-series momentum yields significant returns in 16 markets but this has been reduced to zero when all stocks are included in the portfolios. These findings should not be surprising and highlight that more information is to be found in the tails of the distribution of past returns and this rapidly degrades as one venture further into the middle of the distribution. The other important insight provided by the analysis is that time-series momentum provides the superior performance when the tighter cut-offs are used but that this advantage also dissipates as the cut-offs are relaxed. For an optimal implementation and 32% cut-offs, time-series momentum displays significant outperformance in 13 markets but this is reduced to a handful of markets when 100% of the stocks are included in the portfolios.

Table 4: Momentum Performance under Various Cut-offs

This table reports in columns 3, 4 and 5, the number of markets that report positive momentum returns under best, median and worst implementations for four sets of cut-offs. Columns 6, 7 and 8 reports the average monthly return of the momentum strategies (and their significance) across the 24 markets of the various implementations and cut-offs. Superscripts 1, 5 and 10 are indicative of significance at the 1%, 5% and 10% levels, respectively.

% of stocks in either winner or loser portfolio	Implem-entation	No. of markets with positive returns (significant at 10% or better level)			Average return across the 24 markets (% per month)		
		Time-series momentum (TSM)	Cross sectional momentum (CSM)	TSM - CSM	Time-series momentum (TSM)	Cross sectional momentum (CSM)	TSM – CSM
32%	Best	24 (24)	24 (20)	24 (13)	2.09^{1}	1.43^{1}	0.66^{10}
	Median	24 (16)	22 (14)	19 (4)	0.89^{1}	0.69^{1}	0.19^{5}
	Worst	7 (0)	8 (0)	9 (2)	-0.29	-0.27	-0.02
60%	Best	24 (24)	24 (22)	21 (9)	1.45^{1}	1.14^{1}	0.31
	Median	24 (14)	22 (11)	18 (7)	0.69^{1}	0.52^{10}	0.17
	Worst	8(0)	5(3)	14(0)	-0.17	-0.25	0.08
100% (0% cut-off)	Best	24 (21)	24 (21)	22 (7)	0.97^{1}	0.79^{1}	0.17
	Median	21 (0)	20 (0)	15 (10)	0.37	0.36	0.01
	Worst	2(0)	3(0)	7(0)	-0.22	-0.31	0.09
100% (index cut-off)	Best	24 (21)	24 (22)	14 (3)	0.89^{1}	0.85^{1}	0.04
	Median	23 (0)	23 (0)	12 (1)	0.33	0.33	0.00
	Worst	6(0)	3(0)	15(0)	-0.37	-0.33	-0.04

With the best implementation, both strategies generate significant positive average returns across the 24 markets irrespective of the cut-off employed although we do see that the level of these positive returns fall by something approaching 50% as one moves from a 32% cut-off to a 100% cut-off. With median implementation, we continue to see significant profits still being earned with both 32% and 60% cut-offs but there are no significant profits realised where the cut-offs are extended so that all stocks are included in either the winner or loser portfolios. With the worst implementations, none of the momentum strategies yield positive average returns across the 24 markets under any of the cut-offs examined with the average return across the 24 markets for both momentum strategies being negative for all cut-offs examined.

Perhaps the most interesting findings relate to the relative performance of the two momentum strategies. We report that time-series momentum significantly outperforms cross sectional momentum under a 32% cut-off. Indeed, the evidence suggests that time-series momentum is the superior strategy when well implemented and this is something that we further investigate below.

5.4. Time-series and Cross-sectional Momentum: Absolute and Relative Performance

In this section we will pursue some explanations for the relative good performance of both momentum strategies with particular attention being given to why time-series momentum might outperform cross sectional momentum when optimally implemented.

5.4.1. Portfolio Characteristics of time-series and cross sectional momentum portfolios

In Table 5, we present information on size, book-to-market and momentum characteristics of the two momentum strategies under the optimal implementation, with these characteristics are best considered reference to their average values, reported in Table 1.

Table.5: Basic Characteristics of Optimal Time-Series and Cross-Sectional Momentum

This table displays the average monthly market value (MV), book-to-market (B/M) ratio and ex ante returns (returns over the last six months) of stocks being selected in loser and winner portfolios of time-series (TSM) and cross-sectional (CSM) momentum strategies based on "optimal" implementation approaches from Table 3 for each market.

	TSM						CSM					
	MV		B/M ratio		Return over last 6 months		MV		B/M ratio		Return over last 6 months	
	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner
AUSTRALIA	72.66	268.74	0.48	0.53	-6.56%	9.79%	263.40	476.18	0.79	0.51	-6.04%	9.46%
AUSTRIA	322.45	1269.17	1.10	0.91	-3.90%	4.34%	353.20	946.41	1.43	1.09	-3.53%	4.18%
BELGIUM	492.18	2706.10	2.93	0.74	-3.29%	4.01%	617.22	2419.96	2.16	0.72	-3.03%	3.91%
CANADA	202.29	578.39	1.06	0.64	-5.95%	10.13%	303.40	661.08	1.21	0.61	-5.80%	10.12%
DENMARK	1777.93	6341.44	0.99	0.68	-4.55%	5.61%	1853.03	6094.82	0.99	0.70	-4.18%	5.24%
FINLAND	633.56	2554.76	0.90	0.48	-3.99%	5.58%	729.38	2225.25	0.85	0.51	-3.14%	5.10%
FRANCE	548.94	1226.26	0.88	0.65	-4.88%	6.23%	582.84	1248.64	0.90	0.65	-4.59%	6.16%
GERMANY	243.35	1627.88	3.44	1.14	-5.70%	5.63%	280.77	1484.50	2.97	1.14	-5.05%	5.44%
GREECE	240.11	2808.42	1.28	0.91	-11.48%	14.82%	786.85	5071.72	1.11	0.92	-8.69%	12.92%
HONGKONG	1613.29	4487.89	1.50	0.94	-6.38%	10.51%	2784.85	6685.21	1.57	1.01	-5.54%	9.41%
IRELAND	359.96	694.42	1.67	0.71	-4.04%	7.65%	426.61	689.72	1.74	0.63	-3.92%	8.03%
ISRAEL	175.41	385.33	0.91	1.81	-5.58%	7.12%	374.23	618.26	3.35	1.46	-4.79%	6.65%
ITALY	15001.24	158131.14	1.54	0.72	-4.02%	4.52%	15999.25	164496.67	1.09	0.73	-3.45%	4.07%
JAPAN	120627.24	148494.96	0.91	0.82	-4.25%	6.03%	157861.38	161095.19	0.96	0.86	-3.87%	5.02%
NETHERLANDS	706.49	2216.26	1.09	0.58	-4.74%	5.46%	953.15	2672.05	1.11	0.78	-4.22%	5.21%
NEWZEALAND	156.62	343.64	1.05	0.69	-4.03%	5.84%	165.89	352.01	1.03	0.67	-3.69%	5.61%
NORWAY	1082.09	4214.57	1.05	0.61	-5.36%	7.41%	1277.06	3999.24	1.19	0.65	-4.82%	7.03%
PORTUGAL	709.60	1422.73	1.37	1.34	-5.79%	8.28%	679.12	1446.84	1.66	1.16	-5.43%	7.62%
SINGAPORE	379.17	878.03	1.17	0.72	-4.60%	7.40%	761.87	1290.33	1.24	0.77	-3.69%	6.28%
SPAIN	1800.53	3260.22	0.81	0.61	-3.97%	4.42%	2885.15	3706.77	0.88	0.67	-3.07%	4.30%
SWEDEN	1028.02	6458.43	1.25	0.53	-6.15%	6.53%	1667.15	7580.89	1.21	0.61	-4.80%	6.36%
SWITZERLAND	1369.29	3182.26	1.17	0.91	-3.09%	4.47%	2044.45	3283.52	1.43	0.93	-2.72%	4.26%
UK	146.32	567.62	0.80	0.53	-5.62%	6.20%	189.10	648.34	0.92	0.54	-5.37%	6.08%
US	1135.56	1919.62	0.74	0.45	-4.53%	7.74%	1389.24	2035.15	0.75	0.46	-4.27%	7.53%

Our first observation is that under both momentum strategies, the loser portfolios consist of stocks that are on average considerably smaller to those included in the winner portfolios. However, the stocks in both the winner and loser portfolios under both strategies are much smaller than the average stock in the market. Perhaps most importantly, the difference between the size of the loser and winner portfolios is greater for time-series momentum than it is for cross-sectional momentum. With respect to book-to-market, with only a very few exceptions we find that the average stock in the loser portfolios is a value stock while it is a growth stock in the case of winner portfolios. Further, the average stock in the loser portfolios under cross-sectional momentum is "cheaper" than it is for time-series momentum but there is little difference in the growth characteristics of the stocks in the winner portfolios under the two methods. Finally, as would be expected the loser (winner) portfolios for both momentum strategies consist of stocks that have been performing extremely poorly (well) over the previous six months. However, the spread in this performance is slightly larger for the time-series momentum portfolios.

In summary under both momentum strategies, the loser portfolios have a small cap, value bias while the winner portfolios have a (weaker) small cap, growth bias. This is consistent with the winner portfolios consisting of stocks which are advanced in their recovery phase while the loser stocks have yet to experience a recovery. As a consequence, it is not surprising that the profits from both momentum strategies typically peak in just a few months suggesting a relatively short holding period. Further, the stocks in the loser portfolio under cross-sectional momentum are both smaller and cheaper than under time-series momentum which might suggest that they are nearer a turnaround point which would eat into momentum profits. The major difference between the characteristics of the momentum portfolios under the median implementation as compared with the best implementation is that winner portfolios have stronger growth characteristics with time-series momentum and weaker growth characteristics with cross-sectional momentum. This is consistent with the winner portfolios under time-series momentum enjoying superior performance in the short term.

5.4.2. Time-series and cross-sectional momentum in "Up" and "Down" markets

Cooper et al. (2004) find momentum profitability depends critically on the state of the market with the momentum strategies in periods following a positive market ("Up" market) yielding higher returns than do momentum strategies in periods following a negative market ("Down" market). In order to see whether this finding might apply to our sample and particularly across both time-series and cross-sectional momentum, we evaluated the performance in both "Up" and "Down" markets of the best implementations for each market on which we reported in Table 3. Following the method employed in Cooper et al. (2004), we defined an "Up"

("Down") month as one in which the market index has risen (fallen) over the previous 12 months[12].

Our findings are summarised in Table 6 where we report the average monthly returns across the 24 markets for both time-series and cross-sectional momentum in both up and down markets[13]. Our findings are consistent with those of Copper et al. (2004) in that the average returns for both time-series and cross sectional momentum are much lower in down markets than they are in up markets. It is not surprising that the performance of both the winner and loser portfolios deteriorate in down markets but the poorer performance of both momentum strategies is due to this deterioration being much greater for the winner portfolios. However, this finding of a deterioration of momentum profits in down markets is not universal as there are seven countries where time-series momentum generates higher returns in down markets (Austria, Germany, Israel, Japan, Norway, Spain and Switzerland) and five countries where cross sectional momentum generates higher returns in down markets (Germany, Israel, Japan, Spain and Sweden).

Table 6: Momentum Performance in Up and Down Markets

This table reports the average monthly performance of time-series and cross-sectional momentum across the 24 markets in both up and down markets. Up and down months are defined in accordance with Cooper et al. (2004) where an up (down) month is one in which the previous 12 month market returns have been positive (negative).

Market State	Time-series Momentum (% per month)			Cross Sectional Momentum (% per month)			TSM – CSM (% pm)
	L	W	W - L	L	W	W - L	
Up(193)	-0.27	2.08	2.35	0.16	1.91	1.75	0.60
Down (59)	-0.56	0.75	1.30	0.01	0.09	0.08	1.22
Down - Up	-0.29	-1.33	-1.05	-0.15	-1.82	-1.67	0.62

[12] We also used the previous three and six month past performance of the relevant index to define "Up" and "Down" markets. One thing this did achieve was to increase the number of "Down" months but the major findings remained unchanged to those reported here.

[13] The information of the performance in each of the individual markets is available in an on-line appendix

We have previously seen that time-series momentum outperforms cross sectional in most markets and we know see that this outperformance is approximately double the level that it is in down markets than it is in up markets. We now see from Table 6 that the major factor contributing to this is the very large deterioration in the performance of the winner portfolios under cross sectional momentum that occurs during down markets. A major reason that we would suggest for this finding is that after a period when markets are falling, cross sectional momentum will be including in its winner portfolio many stocks that have been experiencing poor performance. Across the 24 markets, the percentage of stocks assigned to the winner portfolios during down markets under cross sectional momentum represents 16% of all available stocks as this is the percentage of stocks allocated to the winner (and loser) portfolio each month. Under time-series momentum where stocks are only allocated to the winner portfolio if their past performance exceeds some upper threshold, only 7% of the stocks are assigned to the winner portfolio during down periods. In other words, cross sectional momentum has to dig much deeper to find winner stocks during down markets and this contributes to the relatively poor performance of the winner portfolios during such period.

Before proceeding to the next sub-section we will briefly comment on the implication of our analysis of up and down markets for the Japanese and US markets. We see from Table 7 that cross sectional momentum when applied in Japan under the best implementation does generate a positive return in down market but this is not of a sufficient magnitude to offset the zero profits realised during up markets. We also see from Table 7 that the winner portfolios under both momentum strategies generate similar performance during both up and down markets. Indeed, the superiority of time-series momentum over cross-sectional momentum in Japan is due to the performance of the loser portfolios: The time-series momentum loser portfolio generates a return that is in excess of 1% less in up markets and approximately 0.5% per month less in down months.

Table 7: Performance in Up and Down Markets: Japan and the US

This table reports the average monthly performance of time-series and cross-sectional momentum in the Japanese and US markets in both up and down markets. Up and down months are defined in accordance with Cooper et al. (2004) where an up (down) month is one in which the previous 12 month market returns have been positive (negative).

Market	State	No. of months	Time-series (%)			Cross-sectional (%)			TSM – CSM (%)
			L	W	W- L	L	W	W - L	
Japan	Up	146	-0.88[5]	0.18	1.07[5]	0.15	0.12	-0.04	1.10[1]
	Down	106	-0.46	0.65	1.12[10]	-0.07	0.57	0.63	0.49[10]
US	Up	226	0.89[1]	2.02[1]	1.13[1]	0.90[1]	1.94[1]	1.04[1]	0.09
	Down	26	0.89	-0.44	-1.33	2.61	-0.20	-2.81	1.49

The majority of the momentum studies have applied cross sectional momentum to US data and been in the US market using cross-sectional momentum and have generally found the strategy to be highly profitable. Therefore, it may have come as somewhat a surprise to find that cross-sectional momentum has not generated any outperformance over our sample period in the US market. The evidence provided in Table 7 confirms that cross sectional momentum had added in excess of 1% per month in the US during up markets which is in line with the findings of previous studies. All the damage to momentum profits came in the down markets with cross sectional momentum generating a return of almost -3% per month, much of which is attributable to abysmal performance during the GFC and particularly during the 2009 calendar year.

5.1.3. *The performance of individual time-series and cross-sectional momentum stocks*

The final characteristic of the two momentum strategies that we consider is the performance of the individual stocks included in the winner and loser portfolios. Following the procedure of George and Hwang (2004), we run the following regression:

$$R_{it} = b_{0jt} + b_{1jt}Ln(SIZE)_{i,t-1} + b_{2jt}\, CSH_{it} + b_{3jt}\, CSL_{it} + b_{4jt}\, TSH_{it} + b_{5it}\, TSL_{it} + e_{it} \quad (1)$$

where R_{it} is the return on stock i in month t; Ln (Size) is the market capitalization of stock i at time, t-1; CSH_{it} is a dummy that equals 1 if stock i is in the cross-sectional momentum winner portfolio in month t; CSL_{it} is a dummy that equals 1 if stock i is in the cross-sectional momentum loser portfolio in month t; TSH_{it} is a dummy that equals 1 if stock i is in the time-series momentum winner portfolio in month t; TSL_{it} is a dummy that equals 1 if stock i is in the time-series momentum loser portfolio in month t. The constant, b_{0jt}, is the average monthly returns of a portfolio consisting of stocks that do not appear in either the winner or loser portfolios after hedging out the effect of size, while the coefficient attached to each of the other variables reflects the incremental return attached to that type of stock. For example the coefficient, $b1_{jt}$ represents the return in excess of bo_{jt} that can be earned on the average stock included in a cross-sectional momentum loser portfolio. The other coefficients have similar interpretations[14].

The results of running this regression for each of our 24 markets are reported in Table 8. The first thing to observe is that generally stock selection adds value in both the time-series and cross-sectional momentum strategies with TSH – TSL being positive in all 24 markets and CSH - CSL being positive in all but the Israel market. In the case of time-series momentum, the difference is significant in 18 of the 24 markets while in the case of cross-sectional momentum it is only significant in 12 of the 24 markets. Based on this analysis, time-series momentum is superior to cross-sectional momentum (i.e. TSM – CSM) in 16 of the 24 markets although this difference is only significant in Canada, Ireland and Sweden.

[14] It should be emphasised that the findings only relate to the average performance of the stocks held in the portfolio and not to the performance of the portfolio's themselves. It would only reflect the performance of the portfolios if an equal weight was assigned to each of the stocks included in the portfolio which is not the case in any of our optimum portfolios. Therefore, the findings reflect the contribution to the performance from the stock selection embedded in the momentum strategies but not from the portfolio construction.

Table 8:

Based on an optimal implementation for each market from Table 5, this table reports the comparisons between time-series and cross-sectional momentum strategies simultaneously by applying the regression model as set out in equation (1) using data extending from 1992 to 2012. The Newey–West t-statistics are reported below the coefficients for each market. The reported constant is the average monthly returns of a portfolio consisting of stocks that do not appear in either the winner or loser portfolios that has hedged out the effect of size, while coefficient attached to each of the other variables reflects the incremental return attached to that type of stock. The difference of coefficients between TSH (CSH) and TSL (CSL) dummies represent the return of time-series (cross-sectional) momentum strategy after controlling other explanatory variables. The last column in the table shows the return difference between time-series and cross-sectional momentum strategies.

	INTERCEPT	LN(SIZE)	TSH	TSL	TSH-TSL	CSH	CSL	CSH-CSL	TSM - CSM
AUSTRALIA	2.16%	-0.28%	0.16%	-0.38%	0.54%	0.11%	-0.29%	0.40%	0.13%
	3.5108	*-4.0975*	*0.7190*	*-1.6507*	*1.7547*	*0.5217*	*-1.2086*	*1.2800*	*0.2643*
AUSTRIA	0.13%	0.04%	0.54%	-0.48%	1.01%	0.22%	-0.32%	0.54%	0.48%
	0.5078	*0.6962*	*2.5345*	*-1.4357*	*2.7084*	*1.3683*	*-1.5442*	*1.9021*	*1.0979*
BELGIUM	0.58%	0.01%	0.08%	-0.65%	0.73%	0.50%	-0.63%	1.13%	-0.40%
	3.2368	*0.2327*	*0.4948*	*-2.6299*	*2.2797*	*3.7875*	*-3.2500*	*4.5700*	*-1.0044*
CANADA	3.02%	-0.38%	0.81%	-0.54%	1.36%	-0.05%	-0.28%	0.23%	1.12%
	4.8737	*-5.8566*	*2.8043*	*-2.5526*	*4.0170*	*-0.1777*	*-0.9336*	*0.5128*	*1.6993*
DENMARK	0.53%	0.00%	0.72%	-0.58%	1.30%	0.26%	-0.59%	0.85%	0.45%
	1.4049	*0.0261*	*2.9333*	*-1.8625*	*3.3683*	*1.7455*	*-2.2060*	*2.6499*	*0.7912*
FINLAND	1.59%	-0.08%	0.88%	-0.26%	1.14%	-0.12%	-0.51%	0.39%	0.75%
	2.8623	*-1.2394*	*2.5337*	*-0.6454*	*2.0613*	*-0.4784*	*-1.8844*	*0.9416*	*0.9782*
FRANCE	1.13%	-0.06%	0.26%	-0.21%	0.47%	0.21%	-0.64%	0.86%	-0.38%
	3.6626	*-1.7131*	*2.3510*	*-1.1467*	*2.1558*	*1.7175*	*-3.3963*	*3.4712*	*-1.1839*
GERMANY	0.30%	0.01%	-0.02%	-0.57%	0.56%	0.50%	-0.62%	1.12%	-0.56%
	0.8182	*0.2182*	*-0.1039*	*-2.2611*	*1.9468*	*2.9859*	*-3.3338*	*4.2946*	*-1.4621*
GREECE	1.74%	-0.20%	-0.26%	-0.31%	0.06%	0.53%	-0.48%	1.01%	-0.95%
	1.3042	*-1.4265*	*-0.8129*	*-1.0352*	*0.1394*	*2.6387*	*-1.9528*	*2.9642*	*-1.4876*
HONGKONG	3.15%	-0.27%	-0.01%	-0.84%	0.84%	0.23%	-0.34%	0.57%	0.26%
	2.8421	*-2.5444*	*-0.0282*	*-2.5200*	*1.9562*	*0.8975*	*-1.4733*	*1.4398*	*0.4148*
IRELAND	1.83%	-0.15%	1.08%	-1.65%	2.73%	-0.52%	-0.16%	-0.36%	3.09%
	2.7142	*-1.9075*	*1.7829*	*-2.7683*	*3.3709*	*-1.1407*	*-0.2633*	*-0.5121*	*2.2774*
ISRAEL	1.83%	-0.16%	0.30%	-0.52%	0.81%	-0.11%	-0.20%	0.09%	0.72%
	2.8714	*-2.3818*	*1.1338*	*-1.6885*	*2.2171*	*-0.4762*	*-1.1065*	*0.3174*	*1.3263*
ITALY	0.14%	0.02%	0.14%	-0.29%	0.43%	0.45%	-0.81%	1.26%	-0.83%
	0.2881	*0.6370*	*0.5505*	*-0.7494*	*0.9656*	*2.3639*	*-2.9626*	*3.6397*	*-1.2668*
JAPAN	1.36%	-0.11%	-0.19%	-0.21%	0.02%	0.15%	-0.14%	0.29%	-0.27%
	1.3801	*-1.7007*	*-1.3029*	*-1.5506*	*0.0907*	*1.2143*	*-1.0251*	*1.4787*	*-0.9635*
NETHERLANDS	0.55%	0.04%	0.19%	-1.06%	1.26%	0.47%	-0.64%	1.11%	0.15%
	1.3733	*1.0333*	*0.6553*	*-3.4139*	*3.3356*	*2.1977*	*-2.8840*	*3.2439*	*0.2488*
NEWZEALAND	1.04%	-0.04%	1.13%	-0.70%	1.83%	0.35%	-0.21%	0.57%	1.27%
	2.4823	*-0.5912*	*2.3505*	*-1.9094*	*3.0472*	*1.0297*	*-0.5078*	*1.0386*	*1.2487*
NORWAY	1.67%	-0.11%	0.88%	0.00%	0.88%	0.88%	-0.36%	1.24%	-0.36%
	2.6215	*-1.7511*	*1.8893*	*-0.0025*	*1.2945*	*2.9913*	*-0.9608*	*2.6254*	*-0.3617*
PORTUGAL	1.32%	-0.15%	-0.28%	-0.76%	0.48%	0.45%	0.20%	0.25%	0.23%
	4.6750	*-2.5555*	*-0.6691*	*-1.6214*	*0.7531*	*1.4440*	*0.4539*	*0.4227*	*0.2097*
SINGAPORE	1.69%	-0.14%	0.06%	-0.26%	0.32%	0.25%	-0.51%	0.75%	-0.43%
	1.7763	*-1.5978*	*0.2182*	*-1.0791*	*0.8210*	*1.2001*	*-1.9756*	*1.9542*	*-0.9260*
SPAIN	0.84%	-0.02%	0.50%	-0.36%	0.86%	0.11%	-0.32%	0.43%	0.43%
	1.7785	*-0.3636*	*1.9841*	*-0.9272*	*1.8101*	*0.5983*	*-1.1925*	*1.2944*	*0.6205*
SWEDEN	1.36%	-0.05%	0.56%	-1.47%	2.03%	0.12%	-0.50%	0.62%	1.41%
	1.7787	*-0.7103*	*2.4640*	*-3.5811*	*4.1814*	*0.4737*	*-1.7919*	*1.4902*	*1.9946*
SWITZERLAND	0.75%	0.00%	0.57%	-0.45%	1.01%	0.43%	-0.39%	0.82%	0.19%
	2.4152	*0.0449*	*2.3802*	*-1.9839*	*3.6521*	*3.2176*	*-2.2894*	*3.4199*	*0.4952*
UK	0.35%	0.04%	0.56%	-0.55%	1.11%	0.58%	-0.30%	0.88%	0.23%
	0.8790	*0.9412*	*4.8350*	*-3.5133*	*6.5043*	*3.3687*	*-1.8080*	*3.1691*	*0.6959*
US	2.58%	-0.22%	0.29%	-0.19%	0.48%	0.21%	-0.09%	0.30%	0.18%
	5.8286	*-5.4747*	*1.8937*	*-1.5014*	*2.5519*	*1.5447*	*-0.4918*	*1.3247*	*0.6702*

The results of running this regression for each of our 24 markets are reported in Table 8. The first thing to observe is that generally stock selection adds value in both the time-series and cross-sectional momentum strategies with TSH – TSL being positive in all 24 markets and

CSH - CSL being positive in all but the Israel market. In the case of time-series momentum, the difference is significant in 18 of the 24 markets while in the case of cross-sectional momentum it is only significant in 12 of the 24 markets. Based on this analysis, time-series momentum is superior to cross-sectional momentum (i.e. TSM – CSM) in 16 of the 24 markets although this difference is only significant in Canada, Ireland and Sweden.

Although the findings that both momentum strategies in general outperform with time-series momentum being the superior is maintained in the results reported in Table 8, they are not as strong as those reported in Table 3. As suggested previously, the performance reported in Table 8 only reflects the stock selection element of the momentum strategies while those reported in Table 3 also encompass the value added by portfolio construction. However, what it does confirm is that the difference in the stock selection between the two momentum strategies which introduces a market timing element to time-series momentum does result in it choosing on average better performing stocks. Undoubtedly this is a very important contributing factor to its superior performance.

6. Conclusion

We have had over 20 years of academic papers on cross-sectional momentum whereas time-series momentum is a relatively recent phenomenon. This study focuses on undertaking an exhaustive test of the performance of time-series and cross-sectional momentum in 24 major equity markets and, in particular, providing a detailed comparison of the relative performance of portfolios based on the two forms of momentum.

Over the period from 1992 to 2012, both time-series and cross-sectional momentum strategies have generated significant profits under numerous implementations in almost all of our 24 markets. Indeed for time-series momentum, the majority of the extensive implementations examined (as indicated by the median implementation) realise positive returns in all 24 markets with these returns being significant in 17 of these markets. The equivalent figures for cross-sectional momentum are only slightly inferior with the returns being positive in 22 markets (the exceptions being Japan and Hong Kong) and significant in 14 of these markets.

There is clear evidence from our extensive like-for-like comparisons that time-series momentum produces superior performance to cross-sectional momentum. With the best implementation it outperforms in all markets with this outperformance being significant in 13 of these markets. With median implementation, time-series momentum still maintains superior performance in 19 markets with this superiority being significant in five of these markets. Indeed, there is a gradual degradation in the superiority of time-series momentum as one progresses to inferior implementations.

Although both momentum strategies chose stocks on the basis of past performance and so will hold many stocks in common, we have seen that cross-sectional momentum will dig deeper to find winner when markets are performing poorly and deeper to find losers when markets are performing strongly. We have seen that this results in stocks held under the two momentum strategies taking on different characteristics with time series momentum choosing stocks that are smaller and which enjoy a wider spread in the past returns than is the case for cross-sectional momentum. The outcome is that the average winning (losing) stock across the 24 markets under time-series momentum outperforms (underperforms) the average winning (losing) stock under cross-sectional momentum. In turns, this converts into time-series analysis potentially producing the superior performance although as we have seen this superiority can either be enhanced of depleted by the choice of implementation.

The success of momentum is largely depending on the price of stocks going through both up- and down-cycles (i.e. trending in both directions). The best implementation strategies will be those that produce stocks holdings that are most in tune with these cycles. We evaluated numerous possible implementations and found that across all countries, the combination of wither a nine month or 12 month formation period and a three month holding period produced the better investment outcomes. This is suggestive of a slow adjustment in prices to new information but an eventual over-shooting which is a pattern consistent with models produced by Barberis et al. (1998) and Hong and Stein (1999). Other implementation issues that we examined included the weighting scheme used where inverse volatility or market value weights proved best while the method chosen for rebalancing was found to have little impact on investment outcomes.

This paper provides the first comprehensive study of time-series and cross-sectional momentum as applied to equity markets. It confirms just how widespread is the profitability of these strategies and establishes that time-series momentum offers the better of the two options. An important question that remains is just how attractive are these strategies on a risk-adjusted basis after taking account of the full costs of implementation, which is a question that should be addressed at a later day.

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