Trend salience, investor behaviours and momentum profitability

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Abstract

Trend extrapolation in financial markets has been well documented, however it is contentious as to which trends will be extrapolated or mean reverted. This paper examines whether investors are more likely to extrapolate trends that they perceive to be salient, thereby providing an empirical test of the behavioural models of momentum. We employ an investment strategy that exploits trend salience by considering both the magnitude and the persistence of recent return performance. Consistent with behavioural models of momentum, an investment strategy based on trend salience significantly outperforms traditional momentum strategies and is not explained by the four-factor model. The relative performance of the trend salience signal is robust across different investment horizons and size-sorted portfolios, although is time-varying; the strategy does not outperform momentum in "down" markets or periods of high volatility in the formation period where trends are more difficult to identify.

JEL Classification: G02, G11, G12

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1. Introduction

There is now such voluminous evidence in support of the profitability of momentum strategies that momentum is recognised as the "premier anomaly" (Fama and French, 2008). Despite the weight of evidence supporting momentum, there is no consensus view on the rationale for the existence of momentum returns. In light of the inability of risk-based models to explain momentum (Fama and French, 1996; Grundy and Martin, 2001), behavioural models have been developed to explain this phenomenon. Daniel et al. (1998) propose a feedback model that incorporates investor overconfidence due to biased self-attribution. Hong and Stein (1999) suggest an alternate model and argue a market is made up of two heterogeneous investors; "newswatchers" and "momentum traders" that demonstrate bounded-rationality. A model that incorporates investor forecasts is proposed by Barberis et al. (1998), who suggest investors initially underreact to news due to conservatism, resulting in positive autocorrelation, and ultimately overreact over long periods due to the representative heuristic (Tversky and Kahneman, 1974). Within each of these models, momentum profits and subsequent momentum reversals may be explained by market inefficiency due to either individual investor behaviour (Barberis et al., 1998; Daniel et al., 1998) or market imperfections (Hong and Stein, 1999).

Trend extrapolation is an important feature in each of these behavioural models. In the model proposed by Barberis et al. (1998), successive positive returns are likely to trigger the representative heuristic as investors react to the strength of information rather than its statistical weight (Griffin and Tversky, 1992). In this model, investors may overreact to recent extreme past performance; producing the momentum effect. The momentum traders described by Hong and Stein (1999) are conditioned on past returns; therefore stronger recent performance is likely to facilitate a stronger reaction from these traders. In the Daniel et al. (1998) model, recent strong performance is likely to induce a confirmation bias leading to overconfident/self-biased attribution traders to be more confidence in their stock picking ability, producing a momentum effect. In each case, a stock with strong recent returns is likely to induce a stronger momentum effect than a stock with recent performance that is less extreme.

Evidence of trend extrapolation exists in both psychology and finance settings.[1] Extrapolation may occur as individuals react to the strength of information rather than its statistical weight (Griffin and Tversky, 1992). This process involves investors using the 'law of small numbers' to overestimate the probability of a particular stock belonging to a particular distribution. The extent to which an investor extrapolates a past trend may depend on the salience of that trend. Andreassen (1990) uses laboratory experiments to show that the relative salience of information affects both forecasts of financial time-series and trading behaviour. This result is consistent with Andreassen and Kraus (1990), who argue that investors will only incorporate trends that they perceive to be salient into their forecasts of future prices. Further, Andreassen and Kraus (1990) argue that if the salience of the information used by investors to formalise forecasts increases; this leads to a greater responsiveness to recent changes.

A considerable amount of survey and experimental studies show that past changes in price are positively related to the mean subjective forecast of aggregate stock market returns (DeBondt, 1993; Fisher and Statman, 2000; Qiu and Welch, 2004; Vissing-Jorgensen, 2003). Building on Andreassen and Kraus (1990), an increase in the rate of change of past prices should lead to a greater sensitivity to these changes in future forecasts. It therefore follows that a positive trend that is improving should be more salient, and therefore more likely to be extrapolated, than a positive trend that is deteriorating.

[1] For example see: Choi et al., 2010; Delong et al., 1990; Frankel and Froot, 1988; Fuster et al., 2010; Haruvy, et al., 2007; Smith et al., 1988.

As traditional momentum strategies do not account for the salience of the trend within the formation period, a strategy that identifies winner stocks with recent relative outperformance and loser stocks with recent relative underperformance should outperform the traditional momentum strategy. We examine whether the momentum premium can be improved by including (excluding) stocks with a salient (non-salient) trend. Specifically, we argue that investors will extrapolate a recent trend if they consider that trend to be salient. If a winner (loser) stock is still increasing (decreasing) its performance but experiences recent relative underperformance (outperformance), then traders are less likely to extrapolate that performance. If the recent performance of a winner (loser) stock outperforms (underperforms), then investors are more likely to extrapolate that performance.

Our paper provides an empirical test of the models that propose trend extrapolation. We use the recent trend of "winners" and "losers" during the formation period as a measure of the salience of a trend. Consistent with the predictions of Andreassen and Kraus (1990), we show that stocks with a strengthening trend exhibit stronger price continuations than stocks with a deteriorating trend. We develop an investment strategy based on the salience of a momentum trend whereby the investor purchases salient winners and sells salient losers. This investment strategy significantly outperforms a traditional momentum strategy and is robust to size of the stocks in the sample and a risk based explanation. However, the premium is sensitive to the market state, which suggests the salience of the trend is altered by the condition of the market.

2. Data

The data used in this study is sourced from the Australian Graduate School of Management (AGSM) database and comprises of stocks listed on the Australian Stock Exchange for the period January 1992 to December 2011.[2] We use the 90-day bank bill rate, obtained from the AGSM database to proxy for the risk-free rate. The Australian equity market is used for this study because despite the voluminous literature documenting the success of the momentum trading strategy in Australia, very few previous studies have sought to explain this success or investigate investment strategies that may further improve momentum profitability. The Australian equity market comprises characteristics that differ from other developed markets, such as the United States, most particularly because the market capitalisation, trading and institutional ownership is concentrated amongst a relatively small number of large firms (Gaunt and Gray, 2003). Gallagher and Looi (2006) report that outside the largest 100 listed stocks in Australia, there is a decrease in the degree of analyst coverage, information flows and market efficiency. Given these characteristics, the use of Australian data may provide interesting insights into existing behavioural theories, as splitting our sample at the median of market capitalisation and comparing the evidence of trend extrapolation in both segments of the market provides an indirect test of the argument that experienced traders are less likely to exhibit behavioural biases.[3]

For a stock to be included in the sample it must have been listed for a full 12 months prior to the holding period. After filtering the data, all stocks were ranked based on their market capitalisations as at 31 December of each year. Only stocks that are constituents of the ASX500, which comprises the 500 largest stocks ranked on market capitalisation, are included in the sample. All stocks outside the ASX500 are excluded given the small market

[2] The first year in the sample is 1990, as the 12 month/12 month momentum strategy requires 24 lagged months returns data; the first full calendar year that can be examined is 1992.

[3] For example see: Caginalp et al., 2000; De Bondt, 1993; Edwards, 1968; Greenwood and Nagel, 2008; Smith et al., 1988.

capitalisation and consequent illiquidity of these stocks. Our sample of the 500 largest stocks covers 98.70% of the market capitalisation of all stocks listed on the Australian stock market.

The restriction of our study to the ASX500 is consistent with other studies of momentum in Australia. Hurn and Pavlov (2003) and Li et al. (2014) use a restricted sample of the top 200 stocks; Bettman et al. (2009), Demir et al. (2004) and Marshall and Cahan (2005) restrict their sample to stocks that are approved for short-selling on the Australian Stock Exchange. Brailsford and O'Brien (2008) find an interaction between firm size and momentum in Australian equities; specifically they do not find a momentum premium outside the 500 largest companies. Demir et al. (2004) stress that momentum strategies rely heavily on short selling loser stocks. The short selling of very small, illiquid stocks can incur high transaction costs such as large bid-ask spreads and higher borrowing costs. By restricting our sample to only include the constituents of the ASX500, we limit the potential biases caused by these effects and focus on an implementable trading strategy.[4]

The length of sample period can also impact the results of momentum studies. Brailsford and O'Brien (2008) note that many studies of momentum in Australia use short sample periods of up to one decade. The use of 20 years of data makes this one of the longest studies of momentum in Australia. This long sample period relative to previous Australian studies is important, given prior research demonstrates the relationship between market up and downswings and momentum profits (Cooper et al., 2004; Phua et al., 2010). By using a long sample period, trend salience can be examined over both bull and bear markets, including the impacts of the recent global financial crisis.

[4] As robustness we also test trend salience using the entire sample of all stocks listed on the Australian stock exchange and find results that qualitatively similar to the results for the constituents of the ASX All Ordinaries Index. These results are available from the author on request.

3. Methodology

The construction of the trend salience investment strategies involves a two-step process. First, momentum portfolios are formed using a method consistent with Jegadeesh and Titman (1993, 2001). For each year, stocks in the sample are ranked based on the cumulative returns over the past J months and allocated into quintile portfolios. Stocks that have the highest cumulative returns are allocated to the top quintile and are categorised as winners (W). Stocks with the lowest cumulative returns are allocated to the bottom quintile of stocks and are categorised as losers (L). The second step involves categorising winner (losers) stocks as either salient or non-salient winners (losers) based on the ratio of their past M month to 12 month geometric average rate of return given by:

$$\frac{R_{M,i,t}^{GARR}}{R_{12,i,t}^{GARR}} = \frac{\left[\prod_{t=1}^{M}(1 + R_{i,t-M})\right]^{\frac{1}{M}}}{\left[\prod_{t=1}^{12}(1 + R_{i,t-12})\right]^{\frac{1}{12}}} \tag{1}$$

where $R_{M,i,t}^{GARR}$ is the geometric average rate of return (GARR) over the past M months for stock i as at period t.

The median value of the ratio of M month GARR to 12 month GARR is calculated. If the return of a winner stock has a ratio of the past M month GARR to the past 12 month GARR that is greater than the median, the stock is allocated to the salient winner (SW) portfolio otherwise the stock is allocated to the non-salient winner (NW) portfolio. If the returns of a loser stock has a ratio of the past M month GARR and the past 12 month GARR that is less than the median, the stock is allocated to the salient loser (SL) portfolio otherwise the stock is allocated to the non-salient loser (NL) portfolio. For easy comparison between different portfolio methods, M months are defined as 3, 6 and 9 months. To avoid short-term reversals (Jegadeesh, 1990; Lehmann, 1990) and the bid ask bounce (Lehmann, 1990), the Jegadeesh and Titman

(2001) methodology is adopted and one month is skipped between the formation and holding periods.

Our measure of trend salience is similar to the approach employed by Yu and Chen (2011), who examine a formation strategy that differentiates winner and loser stocks according to whether the trend in the formation period is strengthening or deteriorating. This method has the advantage of identifying the strength of the price signal and hence proxy for the salience of a trend that is more likely to be extrapolated. Our construction of the salient trend portfolios is consistent with Yu and Chen (2011) with one notable difference; Yu and Chen (2011) benchmark SW (SL) and NW (NL) with the ratio of M month GARR and 12 month GARR of one rather than the median. This difference in benchmark is non-trivial; by using a benchmark GARR of one the number of stocks in each portfolio may be highly concentrated depending on the market state, which may bias the results. For example, if the aggregate market return is negative in the most recent M months of the formation period, the rate of change of winners would, on average, be decreasing; however the negative rate of change of the loser stocks would be increasing. This would lead to a larger number of NW and a larger number of SL, with only a small number of stocks in the SW and NL portfolios. In this case, the high concentration of the SW and NL portfolios would result in returns being significantly influenced by idiosyncratic risk. Our use of the median GARR as a benchmark ensures the same number of stocks in each portfolio each month.[5]

To analyse the effects of trend salience in portfolio returns, two trading strategies that utilise this information in the formation period are constructed. The first strategy buys the SW

[5] As a robustness test, we also examine the trend salience strategy using the benchmark of a GARR of one and find results that qualitatively similar to the results reported in this paper. These results are available from the author on request.

portfolio and sells the SL portfolio. As the first strategy involves buying (selling) winner (loser) stocks that display a strengthening trend, the strategy is denoted as the 'salient momentum' strategy. The second strategy buys the NW portfolio and sells the NL portfolio. As the second strategy involves buying (selling) winner (loser) stocks that display a deteriorating trend, this strategy is denoted as the 'non-salient momentum' strategy.

By decomposing the formation period in this way, it can be seen whether trend salience influences investors to extrapolate recent performance. If the salient momentum strategy outperforms the non-salient momentum strategy it implies that investors are sensitive to the strength of the price signal in the formation period. This result would suggest that stocks with a strengthening trend are likely to be extrapolated, which is consistent with the behavioural models that are predicated on short-run correlation of prices.

Grundy and Martin (2001) report that momentum returns cannot be explained by standard risk models. To similarly ensure that the returns generated by our salient momentum strategy can be attributed to behavioural factors outlined above and not the systematic selection of risky stocks, we regress the returns generated by the salient momentum strategy against the Carhart (1997) four factors. To perform these tests, the following equation is estimated:

$$R_{p,t} = \alpha_t + \beta_{1,t}\left[R_{M,t} - R_{F,t}\right] + \beta_{2,t}SMB_t + \beta_{3,t}HML_t + \beta_{4,t}WML_t + \varepsilon_t \qquad (2)$$

where $R_{p,t}$ is the return on investment strategy p at time *t*, and $R_{M,t} - R_{F,t}$, SMB_t, HML_t, WML_t are the excess return on the market and the size, value and momentum factors respectively at time *t*.

4. Results

Table 1 shows the monthly returns for six portfolios with equal-weighted returns; the W and L portfolios with a 12-month formation period; the SW (NW) portfolios, which consists of stocks from the W portfolio where the ratio of the past M-month GARR to 12-month GARR is greater (equal to or less) than the median; the NL (SL) portfolios, which consists of stocks from the L portfolio where the ratio of the past M-month GARR to 12-month GARR is equal to or greater (less) than the median.[6] For brevity we only report the results of the M to 12-month strategies; however we have tested M to 9-month and M to 6-month strategies and found the results to be qualitatively similar.[7]

[TABLE 1 ABOUT HERE]

The results of the portfolio analysis shows that the winner portfolios returns decrease as the length of the holding period increases, whilst the loser portfolios have increasing returns as the holding period increase. This decay is consistent with previous momentum studies (Jegadeesh and Titman, 1993, 2001) and is consistent with the long-run mean reversal in the behavioural models. Consistent with trend salience, SW outperforms NW in each strategy. Further, SL experiences lower returns across all holding periods than the NL portfolio. For example the 6 to 12-month SW portfolio held for 6-months yields a monthly return of 1.47% that is statistically significant at the 1% level; this compares with a 0.71% return for the NW portfolio. This feature is not consigned to the particular strategy or holding period. All SW returns are significant at the 1% level, whilst all NW returns other than 6 to 12 and 9 to 12-month strategy held for 3-months are insignificant from zero. The loser portfolios offer the same pattern of

[6] We use raw returns to construct our salient strategies as we argue that investors extrapolate price changes rather than changes in risk-adjusted prices.

[7] For papers that examine momentum using a 12-month formation period see: Carhart, 1997; Fama and French, 1996; Grinblatt and Moskowitz, 2004; Grundy and Martin, 2001; Moskowitz and Grinblatt, 1999.

returns, whilst all returns are insignificant from zero, across all strategies and holding periods SL yield lower returns than the NL portfolios.

A possible explanation for the outperformance (underperformance) of the SW (SL) portfolios is that these portfolios systematically hold winners (losers) with extreme performance. To examine whether SW and SL simply have extreme past returns, we compare the number of salient and non-salient winners and losers in the extreme deciles of past performance. The number of SW and NW in the winner decile is 24 and 26 respectively and the average number of NL and SL in the loser decile is 24 and 26 respectively. A chi-squared test found no statistical difference between the proportion of salient and non-salient stocks in the extreme deciles of past performance. Further, the difference in average monthly formation period returns between SW and NW is -31 basis points, which indicates that, on average, NW actually have higher formation period returns than SW. However, the difference in average monthly formation period returns between NL and SL is 45 basis points indicating that the SL portfolio has lower returns in the formation period. Taken together, it is clear that the salient portfolios do not systematically include stocks with extreme performance in the formation period.[8]

Table 2 presents the monthly returns from the traditional momentum, salient momentum and non-salient momentum strategies. The traditional momentum strategy uses the Jegadeesh and Titman (2001) methodology. The salient momentum strategy is a zero investment strategy that is long in SW and short in SL, the non-salient momentum strategy is a zero investment strategy that is long in NW and short in NL. Returns for the 3 to 12-month strategies are reported in

[8] To robust test these results, the salient strategy is compared to a momentum strategy where winners and losers are created using deciles rather than quintiles. The trend salience strategy outperforms this 10% momentum strategy at all holding periods. This difference is statistically significant at the 1% level, for the 9 and 12-month holding periods.

Panel A; Panel B reports the returns to the 6 to 12-month strategies and returns of the 9 to 12-month strategies are reported in Panel C. The results show a strong momentum effect for 3, 6 and 9-month holding periods, with the 12-month holding period positive but insignificant from zero. Consistent with trend salience, all salient momentum strategies yield positive monthly returns, significant at the 1% level; whilst none of the non-salient momentum strategies earn significant returns, except for the 6 to 12 and 9 to 12-month held for 3-months which are significant at the 5% level.[9]

[TABLE 2 ABOUT HERE]

The statistically significant predictive power of stocks with increasing rates of return in the formation period suggests investors are conditioned to the salience of a trend. To examine a risk-based explanation for the salience premia, salient momentum and non-salient momentum returns of the 6-to-12 strategies for all holding periods were regressed on the Carhart (1997) factors.[10] If systematic risk explains the salient momentum returns, the alpha values should be zero.

We use the WML factor on the right hand side of the regression to formally test whether the returns to salient momentum strategies earns positive alpha after controlling for the traditional momentum factor. By design however, the momentum factor on the right hand side of the equation will be highly correlated with the left hand variable. As an alternative to the momentum factor, we augment the Fama and French (1993) three factor model with a 52-week

[9] We also test the salience strategies using formation periods of 6 and 9-months. In all cases the salience strategies outperform the traditional momentum strategy. These results are available from the author on request.

[10] O'Brien, Brailsford and Gaunt (2010) find that size, book-to-market and momentum are priced in Australian equities.

high momentum factor.[11] The 52-week high factor can also be thought of as a control for price salience; a positive alpha could imply that a trend is considered salient controlling for the price signal.[12]

Panel A from Table 3 shows that at each holding period, controlling for the systematic risk factors, the alpha for the salient momentum strategy is positive and significant at the 1% level. Salient momentum returns are negatively related to the market and size factors and positively related to the momentum factor. In contrast, the alphas for non-salient momentum strategies are insignificant for the 3 and 6-month holding periods and become negative and significant at the 5% level at 9 and 12-month holding periods. Panel B shows that controlling for the 52-week high increases the alphas of the salience strategies with all significant at the 1% level. Whilst the alphas for the non-salience strategies also increase, all are insignificant from zero except the strategy held for 3-months, which is positive and significant at the 1% level.

The result of the Carhart (1997) regression show three important facts: the first is that the salient momentum strategies generates a positive return even after controlling for momentum, second, the significance of the salient momentum strategy alpha controlling for the 52-week high suggest that trend salience is a separate phenomenon from price salience and third, the negative loading of the salient momentum strategies on the market, size and value factors suggest trend salience is not a proxy for systematic risk. Overall the results of the Carhart (1997) regressions are difficult to reconcile with a risk-based explanation for the salient momentum premium.

[TABLE 3 ABOUT HERE]

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[11] For a discussion on the 52-week high, see George and Huang (2004) in the US market and Marshall and Cahan (2005) in Australia.

[12] Our 52-week high factor is applied using the methodology of George and Huang (2004).

Momentum marginal returns are characterised by short-run continuations for approximately 12-months, followed by long-run reversals after 12-months. We examine whether the salience strategies are less likely to exhibit reversals compared to the non-salience strategies. Table 4 reports the Fama and French (1993) alphas of the marginal returns for the salient and non-salient strategies formed on the past 6-month GARR to past 12-month GARR. Panel A shows the 6 to 12 salient momentum strategy's marginal risk-adjusted returns are positive and significant for the first 10-months. In contrast, only the first 3-months post-formation are significant for the non-salient momentum strategy. The cumulative returns for the trend salience strategy are positive and significant for 60-months post-formation, whilst the non-salience strategy become insignificant after 11-months post formation. A possible explanation for this result is that stocks in the non-salient momentum strategy enter the overreaction phase of momentum earlier than the salient momentum stocks and therefore enter the reversal phase earlier. It is interesting to note that beyond 12 months post-formation, there is no significant difference in the marginal risk adjusted returns of the salient momentum and non-salient momentum strategies. Therefore an alternate interpretation of this result is that during the formation period the salience of the salient momentum strategy's trend is statistically larger than the non-salient momentum trend. As both strategies start to exhibit mean reversion in the holding period, the salience of the respective trends reduces and the statistical difference between them also reduces.

[TABLE 4 ABOUT HERE]

5. Robustness Testing

5.1 Cross-Sectional Regressions

Trend salience has been shown to improve the cross-sectional performance of the traditional momentum strategy. We test whether trend salience has explanatory power in the cross-section of returns beyond other factors identified within the literature. Grinblatt and Moskowitz (2004) demonstrate that consistent performance within the formation periods is important. They find that stocks with consistent good returns in the formation period outperform stocks with equivalent overall performance in the formation period that is driven by a few extraordinary months. Lee and Swaminathan (2000) examine the explanatory power of trading volume and momentum and find that winners with high trading volume experience higher momentum returns. George and Hwang (2004) demonstrate that stocks that are near to their 52-week high have higher expected returns than stocks that are far away from their 52-week high. To date, neither of these factors that have been shown to improve momentum in the United States has been tested in the context of the Australian equity market.

We test the explanatory power of trend salience, consistency and volume in the cross-section of returns. These cross-sectional regressions investigate the additional impact of trend salience on the cross-section of stock returns. To perform these tests, the following equation is estimated:

$$r_i = \propto_i + \beta_1 Size_i + \beta_2 B/M_i + \beta_3 r_{i,t-1,t-12} + \beta_4 GARR_i + \beta_5 D_{CW} + \beta_6 Volume_i + \varepsilon_i \qquad (3)$$

where ri is the monthly return of stock i, Size is the natural log of the market capitalisation of stock *i*, B/M is the book to market ratio, $\mathrm{r}_{\mathrm{t-12,t-1}}$ is the past 12-month returns for stock *i*, GARR is the ratio of the past 6-month geometric average rate of return to the past 12-month geometric average rate of return for stock *i*, DCW is a dummy variable that takes the value of one when at least nine out of the past twelve monthly returns are positive and zero otherwise and Volume is the the monthly average volume divided by the average number of shares in the formation period for stock *i*.

The results of these cross-sectional regressions reported in Table 5 show that the consistency of past performance is positively related to future returns, confirming the earlier evidence provided by Grinblatt and Moskowitz (2004), however there is no relationship between volume and subsequent returns. Confirming the evidence reported in earlier sections of this paper, there is a significant positive relationship between the GARR and subsequent returns, even after controlling for consistency and volume. These results indicate that incorporating trend salience can improve subsequent return performance, even after controlling for other factors that have been show to improve momentum profitability.

[INSERT TABLE 5 ABOUT HERE]

5.1 Trend salience and firm size

Hong et al. (2000) show that information diffusion is slow in small firms; suggesting the momentum premium is driven by small stocks. It is therefore possible that the salient momentum strategy systematically selects small stocks with high expected returns, which will make this strategy difficult to implement with higher trading costs. To test whether this investment strategy is implementable, the sample is split at the median based on market capitalisation and the performance of the 6 to 12 strategy is tested across these two subsamples. We choose to split the sample this way for two reasons, first the top 250 stocks represents 96.53% of the market capitalisation of the ASX500, while the bottom 250 stocks only represent 3.47%. Thus the effect of trend salience on small stocks can be seen in the bottom 250 sample.

By comparing the performance of our salient momentum strategy between the top and bottom 250 stocks within the ASX500, we are also able to undertake an indirect examination of the impact of institutional ownership on our behavioural model of trend extrapolation. Gallagher and Looi (2006) argue that in the Australian equity market, the degree of analyst coverage, information flows and market efficiency are much lower for stocks outside the top 100. We split at the top 250, rather than 100, to ensure an adequate number of stocks in the salient and non-salient portfolios. To the extent that institutional traders are expected to be less likely to extrapolate salient trends, the effect should be stronger in the bottom 250 sample.

Table 6 reports the results of the size splits of the traditional momentum, salient momentum and non-salient momentum strategies. Panel A reports the results using the top 250 stocks in the sample and Panel B reports the results of the bottom 250 stocks in the sample. Whilst the magnitude of the salient momentum premium is larger in the bottom 250 stocks, which is consistent with the predictions of behavioural models, this result is largely due to a stronger momentum effect within that segment of the market. In the sample of the 250 largest stocks, salient momentum outperforms traditional momentum at the 1% confidence level across all holding periods. These results demonstrate that the effect of trend salience is not confined to small stocks and that trend salient strategies provide an implementable trading strategy.

[TABLE 6 ABOUT HERE]

5.2 Hold-Out Periods

To examine the pervasiveness of the outperformance of salient momentum strategies and ensure that our results are not driven by a particular period of the business cycle, we also undertake sub-period analysis to examine the performance of each investment strategy across five-year and ten-year sub-periods. The results of this sub-period analysis are reported in Table 7. The salient momentum strategy yields returns that are significantly greater than the traditional momentum returns for all five-year holding periods except 2007 to 2011. Similarly, salient momentum outperformed traditional momentum in the decade from 1992 to 2001, although the difference between returns on these two strategies was not statistically significant in the second ten year sub-period.

[TABLE 7ABOUT HERE]

5.3 Market State Analysis

Andreassen and Kraus (1990) argue that trend salience is sensitive to the market state. During long and sustained up-markets, the trend is considered more salient and the regressiveness of investors' forecasts are likely to be reduced. Evidence from our sub-period analysis provides formative support for this hypothesis. Whilst the sub-period results show salient momentum strategies consistently outperform traditional momentum, it could be inferred that the performance of the overall market may have an impact on salient momentum and traditional momentum returns, as no salient momentum strategy yielded a significant return in the 2007-2011 sub-period.

To formally test whether trend salience is sensitive to the market state, the Cooper et al. (2004) method is utilised whereby two market states are defined: up markets and down markets. Up markets are defined as periods where the average equity risk premium over the past three years is positive and down markets are defined as periods where the average equity risk premium over the past three years is negative. Phua et al. (2010) confirm the results of Cooper et al. (2004) in Australian equities, however the focus in this study is to examine whether the premium on trend salience varies across market conditions. If trend salience varies across market states, the difference between the returns for the salient strategies and the traditional momentum strategy should be insignificant from zero in down markets.

Table 8 presents the results of the market state analysis for the 6 to 12 strategy. Consistent with prior evidence, traditional momentum returns are shown to be insignificant in down markets across all holding periods (Cooper et al., 2004; Phua et al., 2010). Of particular significance is that salient momentum only outperforms traditional momentum in up markets across all holding periods. This suggests that trend salience is stronger after periods of market gains, consistent with our predictions of trend salience in up and down markets.

[TABLE 8 ABOUT HERE]

Andreassen and Kraus (1990) find that extrapolation of trends is less likely when the variance of past price changes is large. If the increased volatility in down markets causes confusion in the price signal, investors may be unlikely to identify and extrapolate a trend. To examine whether trend salience is sensitive to volatility in the formation period we use two parsimonious proxies for *ex-ante* volatility. The first proxy for *ex-ante* volatility is the squared market return, which is given by:

$$\hat{\sigma}^2_{MKT,t} = \sum_{j=0}^{21} r^2_{MKT,d_{t-1-j}} \tag{4}$$

where $\hat{\sigma}^2_{MKT,t}$ is the sum of squared returns in a month.

Our second signal is return dispersion. The use of return dispersion to proxy for volatility is motivated by Stivers (2003) and Stivers and Sun (2010) who find a positive relationship between return dispersion and future market volatility and return dispersion and future momentum returns respectively. Our return dispersion measure is calculated as the cross-sectional standard deviation of monthly portfolio returns across 25 portfolios sorted on size and book-to-market as follows:

$$RD_t = \sqrt{\left[\frac{1}{n-1}\sum_{i=1}^{n}\left(R_{i,t} - R_{\mu,t}\right)^2\right]} \tag{5}$$

where RD_t is the dispersion measure for month *t*, $R_{i,t}$ is the return of portfolio *i* in month *t* and $R_{\mu,t}$ is the equal-weighted portfolio return of the portfolios in month *t*. We smooth both measures of market volatility by a 12-month moving average. The intuition for using a 12-month moving average is to capture the volatility of returns within the formation period.

We define two market states based on the time series of each measure of volatility. High (Low) volatility is defined as the top (bottom three) quartile(s). If volatile markets reduce the ability of investors to identify a trend, then the difference between the salience and traditional momentum strategy returns should be insignificant during the volatile state. Table 9 shows that when volatility is high in the formation period the subsequent difference between the salient and momentum strategies, except for the 12-month strategy during high return dispersion, disappears. This result demonstrates that extrapolation is more likely to occur during periods when investors a given a clear signal for the trajectory of a trend

[TABLE 9 ABOUT HERE]

6. Summary

Andreassen and Kraus (1990) have identified the conditions in which past returns are likely or unlikely to be extrapolated. They show that if subjects are exposed to a price history that has a clearly identifiable trend, then subjects are likely to extrapolate that trend. The extent that a trend will be extrapolated is determined by how salient that trend appears to the investor. A stock with a strengthening trend in the formation period is likely to have a more salient trend than a stock that has a deteriorating trend in the formation period. Momentum strategies that take advantage of trend salience are likely to outperform strategies that do not account for salience.

We find that a zero investment strategy that exploits the salience of a trend in the formation period earns returns that are significantly higher than the traditional momentum strategies. This result is not explained by the Carhart (1997) four factor model, size of stocks in the portfolio, or extreme performance in the formation period. This result is also robust to other methods that have been shown to outperform the traditional momentum strategy. Whilst the salient momentum returns is strong throughout the sample period, salient momentum strategies do not outperform the traditional momentum strategy when volatility in the formation period is high, consistent with the experimental results of Andreassen and Kraus (1990).

Marginal risk adjusted returns for 60 months after the formation period were also examined, with salient momentum returns significantly positive for 10-months post-formation, compared to only 3-months for the non-salient momentum strategy. The implication of this result is that non-salient stocks may have entered early into the overreaction phase, leading to early reversals or it could demonstrate that trend salience is driving momentum performance, as salience decreases, the level of extrapolation decreases to a point whereby reversals are likely to occur. The evidence of trend salience reported in our paper supports the behavioural models of investor extrapolation.

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Table 1 – Returns of portfolios formed on momentum and trend salience

This table reports the mean monthly returns for portfolios formed on momentum and trend salience across the period 1992-2011. The winner (W) and loser (L) portfolios are the top and bottom performing quintiles based on the past 12-month returns. The salient winner (SW) portfolios include stocks where the ratio of the past M month GARR and the past 12-month GARR is greater than the median. The non-salient winner (NW) portfolios include stocks where the ratio of the past M month GARR and the past 12-month GARR is equal to or less than the median. The non-salient loser (NL) portfolios include stocks where the ratio of the past M month GARR and the past 12-month GARR is equal to or greater than the median. The salient loser (SL) portfolios include stocks where the ratio of the past M month GARR and the past 12-month GARR is less than the median. All portfolios are held for K months, defined as 3, 6, 9 and 12. HAC t-statistics are reported in parentheses under their associated means.

	Portfolios					
	W	SW	NW	L	NL	SL
Panel A: 3 to 12 Strategy						
3	0.0130	0.0176	0.0083	0.0010	0.0032	-0.0011
	(3.10)**	(4.22)**	(1.88)	(0.18)	(0.58)	(-0.18)
6	0.0109	0.0146	0.0072	0.0020	0.0038	0.0003
	(2.63)**	(3.56)**	(1.64)	(0.36)	(0.72)	(0.04)
9	0.0097	0.0129	0.0065	0.0029	0.0046	0.0012
	(2.30)*	(3.17)**	(1.44)	(0.54)	(0.93)	(0.20)
12	0.0088	0.0114	0.0062	0.0042	0.0060	0.0024
	(2.10)*	(2.84)**	(1.39)	(0.82)	(1.26)	(0.44)
Panel B: 6 to 12 Strategy						
3	0.0130	0.0172	0.0088	0.0010	0.0020	0.0000
	(3.10)**	(4.02)**	(2.04)*	(0.18)	(0.37)	(0.01)
6	0.0109	0.0147	0.0071	0.0020	0.0033	0.0007
	(2.63)**	(3.54)**	(1.65)	(0.36)	(0.63)	(0.12)
9	0.0097	0.0125	0.0069	0.0029	0.0050	0.0007
	(2.30)*	(3.04)**	(1.56)	(0.54)	(1.02)	(0.12)

12	0.0088	0.0110	0.0067	0.0042	0.0062	0.0022
	(2.10)*	(2.71)**	(1.50)	(0.82)	(1.30)	(0.39)
Panel C: 9 to 12 Strategy						
3	0.0130	0.0171	0.0089	0.0010	0.0026	-0.0006
	(3.10)**	(4.03)**	(2.07)*	(0.18)	(0.49)	(-0.09)
6	0.0109	0.0138	0.0080	0.0020	0.0042	-0.0002
	(2.63)**	(3.34)**	(1.87)	(0.36)	(0.80)	(-0.02)
9	0.0097	0.0118	0.0076	0.0029	0.0052	0.0005
	(2.30)*	(2.88)**	(1.72)	(0.54)	(1.05)	(0.09)
12	0.0088	0.0105	0.0071	0.0042	0.0061	0.0024
	(2.10)*	(2.62)**	(1.60)	(0.82)	(1.26)	(0.43)

* denotes significant at the 5% level
** denotes significant at the 1% level.

Table 2 – Investment strategy returns

This table reports the monthly returns of three investment strategies formed on the basis of trend salience across the period 1992-2011. The first strategy (MOM) is a momentum strategy that takes a long position in the quintile of "winners" and a short position in the quintile of "losers". The second strategy (SAL) involves buying the SW portfolio and selling the SL portfolio. The third strategy (NON) involves buying the NW portfolio and selling the NL portfolio. SAL-MOM is the difference between the salient momentum and traditional momentum strategies. The HAC t-statistics and monthly Sharpe ratios for each strategy are reported underneath the mean returns.

	Panel A: 3 to 12				Panel B: 6 to 12				Panel C: 9 to 12			
	MOM	SAL	NON	SAL-MOM	MOM	SAL	NON	SAL-MOM	MOM	SAL	NON	SAL-MOM
3	0.0120	0.0188	0.0052	0.0068	0.0120	0.0172	0.0068	0.0052	0.0120	0.0176	0.0063	0.0057
	(3.40)**	(4.14)**	(1.54)	(3.60)**	(3.40)**	(3.61)**	(2.08)*	(2.55)*	(3.40)**	(3.82)**	(2.09)*	(3.38)**
Sharpe	0.27	0.32	0.12		0.27	0.30	0.15		0.27	0.31	0.15	
6	0.0089	0.0143	0.0034	0.0055	0.0089	0.0139	0.0038	0.0051	0.0089	0.0139	0.0038	0.0051
	(2.82)**	(3.56)**	(1.14)	(3.32)**	(2.82)**	(3.33)**	(1.36)	(3.02)**	(2.82)**	(3.55)**	(1.40)	(4.08)**
Sharpe	0.22	0.28	0.09		0.22	0.28	0.10		0.22	0.29	0.10	
9	0.0068	0.0117	0.0019	0.0049	0.0068	0.0118	0.0018	0.0050	0.0068	0.0113	0.0023	0.0045
	(2.48)*	(3.34)**	(0.74)	(3.52)**	(2.48)*	(3.35)**	(0.74)	(3.67)**	(2.48)*	(3.43)**	(0.93)	(4.43)**
Sharpe	0.18	0.26	0.05		0.18	0.27	0.05		0.18	0.26	0.07	
12	0.0046	0.0090	0.0002	0.0044	0.0046	0.0088	0.0004	0.0042	0.0046	0.0082	0.0010	0.0036
	(1.90)	(3.05)**	(0.09)	(3.82)**	(1.90)	(3.01)**	(0.17)	(3.81)**	(1.90)	(2.93)**	(0.44)	(4.18)**
Sharpe	0.14	0.22	0.01		0.14	0.22	0.01		0.14	0.21	0.03	

* denotes significant at the 5% level

** denotes significant at the 1% level.

Table 3 – Four-factor model regression analysis

This table reports the coefficients of the Carhart [1997] four factor model over the period from January 1992 to December 2011. The model that is estimated is given as follows:

$$R_{p,t} = \alpha_t + \beta_{1,t}\left[R_{M,t} - R_{F,t}\right] + \beta_{2,t}SMB_t + \beta_{3,t}HML_t + \beta_{4,t}WML_t + \varepsilon_t$$

where $R_{p,t}$ is the return on investment strategy p at time t, and $R_{M,t} - R_{F,t}$, SMB_t, HML_t, WML_t are the excess return on the market and the size, value and momentum factors respectively. Panel B report the results where the WML factor is replaced by the 52-week high factor. Results are reported for two different investment strategies as the dependent variable, which are created using a double sort on momentum and trend salience. Salient momentum strategies are formed by the SW portfolio and taking a short position in the SL portfolio. Non-salient momentum strategies are formed by taking a long position in the NW portfolio and taking a short position in NL portfolio. HAC adjusted t-statistics are reported in parenthesis below their associated coefficients.

	α	β_1	β_2	β_3	β_4	Adj. R^2
Panel A						
3-Month Holding						
Non-salient	0.0008	-0.0146	-0.0527	-0.0138	0.4984	0.50
	(0.37)	(-0.29)	(-1.31)	(-0.21)	(14.27)**	
Salient	0.0064	-0.0677	-0.0478	0.0472	0.8133	0.75
	(3.19)**	(-1.44)	(-1.27)	(0.76)	(24.95)**	
6-Month Holding						
Non-salient	-0.0015	0.0112	-0.0124	0.0730	0.5400	0.62
	(-0.93)	(0.30)	(-0.42)	(1.50)	(18.65)**	
Salient	0.0070	-0.0748	-0.0815	-0.0373	0.7959	0.78
	(4.31)**	(-1.95)	(-2.62)**	(-0.74)	(26.70)**	
9-Month Holding						
Non-salient	-0.0027	0.0349	0.0151	0.0720	0.5888	0.69
	(-2.13)*	(1.13)	(0.60)	(1.76)	(22.04)**	
Salient	0.0077	-0.0825	-0.0960	-0.0674	0.7824	0.81
	(5.84)**	(-2.60)**	(-3.71)**	(-1.60)	(28.42)**	
12-Month Holding						
Non-salient	-0.0023	0.0388	0.0207	0.0507	0.6270	0.75
	(-2.13)*	(1.48)	(0.97)	(1.46)	(25.27)**	
Salient	0.0069	-0.0537	-0.0968	-0.0540	0.7753	0.84
	(6.42)**	(-2.04)*	(-4.48)**	(-1.54)	(31.02)**	

Panel B						
3-Month Holding						
Non-salient	0.0061	-0.0108	-0.1507	-0.3284	0.5958	0.46
	(2.77)**	(-0.17)	(-2.64)**	(-4.03)**	(11.03)**	
Salient	0.0155	-0.2289	-0.2436	-0.3441	0.8529	0.56
	(4.86)**	(-3.58)**	(-5.43)**	(-3.39)**	(7.73)**	
6-Month Holding						
Non-salient	0.0035	-0.0025	-0.1305	-0.2731	0.4638	0.35
	(1.55)	(-0.04)	(-2.58)*	(-3.20)**	(9.06)**	
Salient	0.0137	-0.1543	-0.2838	-0.4148	0.7396	0.61
	(5.68)**	(2.89)**	(-7.25)**	(-4.64)**	(8.79)**	
9-Month Holding						
Non-salient	0.0019	-0.0086	-0.1154	-0.2526	0.3646	0.28
	(0.83)	(-0.14)	(-2.69)**	(2.76)**	(7.39)**	
Salient	0.0123	-0.1050	-0.3008	-0.4198	0.6256	0.61
	(6.13)**	(-2.36)*	(-7.74)**	(-5.57)**	(9.61)**	
12-Month Holding						
Non-salient	0.0008	0.0013	-0.1151	-0.2420	0.2945	0.24
	(0.37)	(0.02)	(-2.92)**	(-2.83)**	(5.98)**	
Salient	0.0093	-0.0679	-0.2826	-0.3572	0.5329	0.56
	(5.31)**	(-1.47)	(-7.41)**	(-5.03)**	(9.95)**	

* denotes significant at the 5% level
** denotes significant at the 1% level.

Table 4 – Marginal returns to trend salient strategies after portfolio formation

This table presents the marginal and cumulative Fama and French (1993) three factor alphasfor the salient momentum strategy (Panel A) and the non-salient momentum strategy (Panel B) in each month following the formation period. Salient momentum strategies are formed by taking a long position in the SW portfolio and a short position in the SL portfolio from the previous year. Non-salient momentum strategies are formed by taking a long position in the NW portfolio and a short position in the NL portfolio from the previous year. HAC t-statistics are in parenthesis underneath their associated mean values.

Panel A: Salient momentum marginal returns

	Marginal	Cumulative		Marginal	Cumulative		Marginal	Cumulative
1	0.0289		21	-0.0004	0.1656	41	0.0013	0.1942
	(6.14)**			(-0.14)	(4.35)**		(0.53)	(3.55)**
2	0.0246	0.0536	22	0.0022	0.1679	42	0.0024	0.1967
	(5.57)**	(6.00)**		(0.86)	(4.31)**		(0.88)	(3.58)**
3	0.0190	0.0726	23	0.0023	0.1702	43	0.0033	0.2000
	(4.78)**	(5.73)**		(0.76)	(4.25)**		(1.37)	(3.62)**
4	0.0186	0.0912	24	-0.0006	0.1697	44	-0.0012	0.1989
	(4.81)**	(5.66)**		(-0.21)	(4.12)**		(-0.44)	(3.57)**
5	0.0188	0.1100	25	-0.0015	0.1682	45	-0.0003	0.1986
	(5.54)**	(5.92)**		(-0.49)	(3.94)**		(-0.10)	(3.51)**
6	0.0184	0.1284	26	-0.0024	0.1658	46	-0.0041	0.1945
	(5.80)**	(6.27)**		(-0.73)	(3.75)**		(-1.28)	(3.38)**
7	0.0197	0.1482	27	-0.0011	0.1647	47	-0.0061	0.1884
	(5.61)**	(6.59)**		(-0.37)	(3.60)**		(-2.15)*	(3.23)**
8	0.0156	0.1637	28	0.0004	0.1651	48	-0.0062	0.1822
	(4.72)**	(6.80)**		(0.13)	(3.51)**		(-2.53)*	(3.10)**
9	0.0127	0.1764	29	0.0005	0.1656	49	-0.0064	0.1759
	(3.94)**	(6.94)**		(0.15)	(3.40)**		(-2.67)**	(2.97)**
10	0.0083	0.1847	30	0.0026	0.1682	50	-0.0085	0.1674
	(2.60)**	(6.99)**		(0.86)	(3.38)**		(-3.49)**	(2.78)**
11	0.0038	0.1885	31	0.0051	0.1734	51	-0.0063	0.1611
	(1.22)	(6.90)**		(1.84)	(3.46)**		(-2.32)*	(2.63)**
12	-0.0017	0.1869	32	0.0058	0.1792	52	-0.0059	0.1552
	(-0.52)	(6.60)**		(2.28)*	(3.54)**		(-2.21)*	(2.50)*
13	-0.0013	0.1856	33	0.0031	0.1822	53	-0.0051	0.1501
	(-0.39)	(6.36)**		(1.04)	(3.54)**		(-2.21)*	(2.38)*
14	-0.0032	0.1824	34	0.0024	0.1847	54	-0.0052	0.1449
	(-0.88)	(5.99)**		(0.92)	(3.53)**		(-1.95)	(2.25)*
15	-0.0031	0.1793	35	0.0033	0.1880	55	-0.0017	0.1433
	(-0.93)	(5.64)**		(1.29)	(3.56)**		(-0.69)	(2.19)*
16	-0.0042	0.1751	36	0.0015	0.1895	56	-0.0006	0.1427
	(-1.25)	(5.30)**		(0.50)	(3.54)**		(-0.22)	(2.14)*
17	-0.0033	0.1718	37	0.0023	0.1916	57	-0.0000	0.1427
	(-1.00)	(5.00)**		(0.89)	(3.55)**		(-0.01)	2.12)*
18	-0.0017	0.1700	38	0.0015	0.1932	58	0.0029	0.1455
	(-0.60)	(4.83)**		(0.64)	(3.53)**		(1.27)	(2.14)*
19	-0.0017	0.1683	39	-0.0004	0.1929	59	0.0038	0.1493
	(-0.54)	(4.67)**		(-0.17)	(3.52)**		(1.62)	(2.18)*
20	-0.0023	0.1660	40	0.0000	0.1929	60	0.0022	0.1515
	(-0.69)	(4.48)**		(0.03)	(3.52)**		(0.82)	(2.19)*

Panel B: Non-salient momentum marginal returns

1	0.0174		21	0.0007	0.0225	41	-0.0023	0.0455
	(5.31)**			(0.24)	(0.51)		(-0.83)	(0.76)
2	0.0123	0.0297	22	-0.0016	0.0208	42	-0.0041	0.0415
	(3.63)**	(4.60)**		(-0.53)	(0.46)		(-1.34)	(0.69)
3	0.0082	0.0379	23	-0.0021	0.0187	43	-0.0049	0.0365
	(2.51)*	(4.07)**		(-0.68)	(0.40)		(1.53)	(0.60)
4	0.0059	0.0438	24	0.0013	0.0200	44	-0.0065	0.0300
	(1.82)	(3.66)**		(0.44)	(0.42)		(-2.19)*	(0.49)
5	0.0044	0.0482	25	0.0032	0.0233	45	-0.0063	0.0237
	(1.41)	(3.34)**		(1.12)	(0.47)		(-2.35)*	(0.38)
6	0.0036	0.0518	26	0.0032	0.0264	46	-0.0055	0.0182
	(1.04)	(3.06)**		(1.15)	(0.52)		(-2.48)*	(0.29)
7	0.0012	0.0530	27	0.0025	0.0289	47	-0.0035	0.0147
	(0.36)	(2.75)**		(0.89)	(0.56)		(-1.51)	(0.23)
8	0.0004	0.0534	28	0.0017	0.0306	48	-0.0036	0.0111
	(0.11)	(2.48)*		(0.60)	(0.58)		(-1.40)	(0.17)
9	-0.0007	0.0527	29	0.0017	0.0323	49	-0.0040	0.0071
	(-0.19)	(2.20)*		(0.65)	(0.61)		(-1.39)	(0.11)
10	0.0003	0.0531	30	0.0014	0.0337	50	-0.0042	0.0029
	(0.10)	(2.02)*		(0.60)	(0.63)		(-1.70)	(0.04)
11	-0.0005	0.0525	31	0.0019	0.0357	51	-0.0051	-0.0023
	(-0.15)	(1.84)		(0.76)	(0.65)		(-2.18)*	(-0.03)
12	-0.0044	0.0481	32	0.0019	0.0376	52	-0.0001	-0.0024
	(-1.35)	(1.56)		(0.64)	(0.67)		(-0.07)	(-0.04)
13	-0.0025	0.0456	33	0.0017	0.0393	53	-0.0007	-0.0031
	(-0.90)	(1.42)		(0.62)	(0.70)		(-0.31)	(-0.05)
14	-0.0054	0.0403	34	0.0017	0.0409	54	0.0001	-0.0030
	(-1.62)	(1.20)		(0.67)	(0.72)		(0.05)	(-0.04)
15	-0.0066	0.0337	35	0.0002	0.0411	55	-0.0006	-0.0036
	(-1.94)	(0.97)		(0.07)	(0.72)		(-0.28)	(-0.05)
16	-0.0043	0.0294	36	0.0012	0.0423	56	-0.0037	-0.0073
	(-1.33)	(0.82)		(0.50)	(0.73)		(-1.72)	(-0.10)
17	-0.0049	0.0245	37	0.0019	0.0443	57	-0.0019	-0.0092
	(-1.39)	(0.66)		(0.82)	(0.76)		(-0.97)	(-0.13)
18	-0.0016	0.0229	38	-0.0002	0.0441	58	-0.0018	-0.0111
	(-0.49)	(0.59)		(-0.07)	(0.75)		(-0.94)	(-0.16)
19	0.0004	0.0233	39	0.0034	0.0475	59	-0.0033	-0.0143
	(0.14)	(0.58)		(1.16)	(0.81)		(-1.66)	(-0.20)
20	-0.0016	0.0217	40	0.0003	0.0478	60	-0.0014	-0.0157
	(-0.45)	(0.52)		(0.11)	(0.81)		(-0.68)	(-0.22)

* denotes significant at the 5% level

** denotes significant at the 1% level.

Table 5: Cross-Sectional Regressions

Cross-sectional regressions are run every month on the largest 500 stocks for the period January 1992 to December 2011. Monthly stock returns are regressed on Size (natural log of market capitalisation), B/M (natural log of book to market ratio), $r_{t-12,t-1}$ (past 12-month returns), GARR (the ratio of the past 6-month geometric average rate of return to the past 12-month geometric average rate of return), D^{CW} (A dummy variable that takes the value of 1 when 9 out of the past 12 monthly returns are positive) and Volume (measure as the monthly average volume divided by the average number of shares in the formation period).

Variable	Model 1	Model 2	Model 3	Model 4
Size	-0.0064	-0.0097	-0.0089	-0.0087
	(-2.37)*	(-3.49)**	(-3.08)**	(-3.16)**
B/M	0.0093	0.01154	0.0126	0.0124
	(3.51)**	(3.93)**	(3.90)**	(4.09)**
$\boldsymbol{r_{t-12,t-1}}$	0.0031	-0.0123	0.0061	0.0071
	(0.35)	(-1.15)	(0.49)	(0.66)
GARR	0.9686			0.9725
	(7.26)**			(7.08)**
$\mathbf{D^{CW}}$		0.0730		0.0573
		(12.98)**		(7.02)**
Volume			0.0007	0.0006
			(0.96)	(0.83)

* denotes significant at the 5% level
** denotes significant at the 1% level.

Table 6 – Salient momentum returns across sub-samples formed on market capitalisation

This table shows monthly returns to the traditional momentum, salient momentum, non-salient momentum strategies and monthly Sharpe ratios for the period 1992-2011 with HAC t-statistics in parenthesis. Salient momentum strategies are formed by taking a long position in the SW portfolio and a short position in the SL portfolio from the previous year. Non-salient momentum strategies are formed by taking a long position in the NW portfolio and a short position in the NL portfolio from the previous year. The momentum strategies are formed using the Jegadeesh and Titman [1993] equal-weighted portfolios using a 12 month/K month strategy where K months are the holding periods, defined as 3, 6, 9 and 12. Panel A reports the monthly returns for a sub-sample consisting of the 250 largest stocks in the sample and Panel B reports the monthly returns for a sub-sample of the 250 smallest stocks in the sample.

Holding Period	MOM	SAL	NON	SAL-MOM
Panel A: Top 250				
3	0.0115	0.0171	0.0059	0.0056
	(3.35)**	(3.69)**	(1.95)	(2.97)**
Sharpe	0.25	0.31	0.13	
6	0.0084	0.0143	0.0024	0.0060
	(2.67)**	(3.29)**	(0.93)	(3.45)**
Sharpe	0.20	0.27	0.06	
9	0.0058	0.0114	0.0002	0.0056
	(2.11)*	(3.17)**	(0.07)	(4.22)**
Sharpe	0.15	0.25	0.00	
12	0.0036	0.0084	-0.0012	0.0048
	(1.46)	(2.74)**	(-0.55)	(4.15)**
Sharpe	0.10	0.20	-0.04	
Panel B: Bottom 250				
3	0.0127	0.0188	0.0065	0.0062
	(3.22)**	(3.55)**	(1.56)	(2.29)*
Sharpe	0.24	0.27	0.12	
6	0.0095	0.0147	0.0042	0.0052
	(2.68)**	(3.17)**	(1.23)	(2.54)*
Sharpe	0.20	0.25	0.09	
9	0.0074	0.0121	0.0028	0.0047
	(2.38)*	(2.99)**	(0.92)	(2.71)**
Sharpe	0.17	0.23	0.06	
12	0.0055	0.0092	0.0019	0.0036
	(2.00)*	(2.67)**	(0.68)	(2.56)*
Sharpe	0.14	0.19	0.05	

* denotes significant at the 5% level
** denotes significant at the 1% level.

Table 7 – Sub-sample analysis of trend salient strategies

This table shows monthly returns to the traditional momentum, salient momentum and non-salient momentum strategies within four, 5-year and two, 10-year sub-periods. The sample period is January 1992 to December 2011. Salient momentum strategies are formed by taking a long position in the SW portfolio and a short position in the SL portfolio from the previous year. Non-salient momentum strategies are formed by taking a long position in the NW portfolio and a short position in the NL portfolio from the previous year. The traditional momentum strategies are formed using the Jegadeesh and Titman [1993] equal-weighted portfolios using a 12-month/K month strategy where K months are the holding periods, defined as 3, 6, 9 and 12. HAC t-statistics are reported in parenthesis beside their associated mean values.

	MOM	SAL	NON	SAL-MOM
1992-1996				
3	0.0050 (1.92)	0.0118 (3.43)**	-0.0017 (-0.47)	0.0068 (2.81)**
6	0.0020 (0.77)	0.0070 (2.56)*	-0.0029 (-0.86)	0.0050 (2.99)**
9	-0.0002 (-0.05)	0.0024 (0.82)	-0.0027 (-0.80)	0.0026 (1.72)
12	-0.0012 (-0.42)	0.0005 (0.17)	-0.0030 (-0.85)	0.0011 (1.39)
1997-2001				
3	0.0192 (3.00)**	0.0296 (3.34)**	0.0087 (1.32)	0.0105 (2.33)**
6	0.0133 (2.52)*	0.0242 (3.41)**	0.0024 (0.46)	0.0109 (3.27)**
9	0.0090 (1.94)	0.0197 (3.18)**	-0.0015 (-0.32)	0.0106 (3.85)**
12	0.0057 (1.38)	0.0146 (2.74)**	-0.0032 (-0.77)	0.0089 (3.67)**
2002-2006				
3	0.0184 (3.33)**	0.0214 (3.53)**	0.0153 (2.73)**	0.0030 (1.60)
6	0.0160 (3.35)**	0.0210 (3.81)**	0.0110 (2..42)*	0.0050 (3.06)**
9	0.0136 (3.27)**	0.0195 (3.72)**	0.0078 (2.24)*	0.0059 (3.85)**
12	0.0104 (2.73)**	0.0151 (3.12)**	0.0057 (1.79)	0.0047 (3.12)**
2007-2011				
3	0.0053 (0.54)	0.0059 (0.43)	0.0047 (0.60)	0.0006 (0.11)
6	0.0042 (0.46)	0.0036 (0.29)	0.0048 (0.64)	-0.0006 (-0.14)
9	0.0046 (0.60)	0.0054 (0.56)	0.0039 (0.54)	0.0008 (0.22)
12	0.0035 (0.52)	0.0050 (0.64)	0.0021 (0.32)	0.0014 (0.56)
1992-2001				
3	0.0121 (3.23)**	0.0207 (4.03)**	0.0035 (0.88)	0.0086 (3.25)**
6	0.0077 (2.42)*	0.0156 (3.69)**	-0.0002 (-0.08)	0.0079 (3.95)**
9	0.0045 (1.54)	0.0111 (2.85)**	-0.0021 (-0.73)	0.0066 (3.64)**
12	0.0022 (0.84)	0.0075 (2.25)*	-0.0031 (-1.11)	0.0053 (3.38)**
2002-2011				
3	0.0118 (1.96)	0.0137 (1.70)	0.0100 (1.97)	0.0018 (0.61)
6	0.0101 (1.84)	0.0123 (1.68)	0.0079 (1.77)	0.0022 (0.84)
9	0.0091 (1.97)	0.0125 (2.09)*	0.0058 (1.47)	0.0033 (1.66)
12	0.0070 (1.73)	0.0100 (2.06)*	0.0039 (1.06)	0.0031 (1.96)

* denotes significant at the 5% level

** denotes significant at the 1% level.

Table 8 – Trend salient strategies in up and down markets

This table shows monthly returns to the traditional momentum, salient momentum and non-salient momentum strategies within up and down markets. Up markets are defined as periods where the average equity risk premium over the past three years is positive and down markets are defined as periods where the average equity risk premium over the past three years is negative. Salient momentum strategies are formed by taking a long position in the SW portfolio and a short position in the SL portfolio from the previous year. Non-salient momentum strategies are formed by taking a long position in the NW portfolio and a short position in the NL portfolio from the previous year. The traditional momentum strategies are formed using the Jegadeesh and Titman [1993] equal-weighted portfolios using a 12 month/K month strategy where K months are the holding periods. Mean monthly returns are reported for investment strategies with a 3, 6, 9 and 12-month holding period. The HAC t-statistics (T-stat) and number of observations (Obs) are reported underneath their associated mean values.

		MOM	SAL	NON	SAL-MOM
3-month					
Down	Return	-0.0016	-0.0011	-0.0021	0.0005
	T-stat	(-0.25)	(-0.12)	(-0.34)	(0.13)
	Obs	62	62	62	62
Up	Return	0.0167	0.0235	0.0099	0.0068
	T-stat	(5.28)**	(6.02)**	(3.15)**	(4.28)**
	Obs	178	178	178	178
6-month					
Down	Return	-0.0019	-0.0036	-0.0003	-0.0017
	T-stat	(-0.32)	(-0.47)	(-0.04)	(-0.52)
	Obs	62	62	62	62
Up	Return	0.0126	0.0200	0.0053	0.0074
	T-stat	(4.53)**	(6.00)**	(1.93)	(5.97)**
	Obs	178	178	178	178
9-month					
Down	Return	-0.0004	-0.0014	0.0006	-0.0010
	T-stat	(-0.07)	(-0.22)	(0.11)	(-0.43)
	Obs	62	62	62	62
Up	Return	0.0093	0.0164	0.0023	0.0070
	T-stat	(3.63)**	(5.33)**	(0.92)	(6.49)**
	Obs	178	178	178	178
12-month					
Down	Return	-0.0005	-0.0007	-0.0003	-0.0002
	T-stat	(-0.10)	(-0.13)	(-0.05)	(-0.14)
	Obs	62	62	62	62
Up	Return	0.0064	0.0121	0.0006	0.0057
	T-stat	(2.69)**	(4.27)**	(0.29)	(5.87)**
	Obs	178	178	178	178

* denotes significant at the 5% level

** denotes significant at the 1% level.

Table 9 – Trend salience and volatility

This table shows outperformance of the salience strategies against the benchmark traditional momentum strategy during periods of formation period volatility. Formation period volatility is defined as the 12-month moving average of return dispersion (RD) and the 12-month moving average of realised volatility (MKT^2). Periods of "High" volatility are defined as the top quartile of return dispersion and realised volatility "Low" volatility is defined as the bottom three quartiles. The t-statistics (T-stat) are reported underneath their associated mean values.

			SAL-MOM RD	SAL-MOM MKT^2
3-months				
	High	Returns	0.0024	0.0007
		T-stat	(0.55)	(0.17)
	Low	Returns	0.0062	0.0061
		T-stat	(3.99)**	(3.59)**
6-months				
	High	Returns	0.0036	-0.0011
		T-stat	(1.00)	(-0.32)
	Low	Returns	0.0055	0.0073
		T-stat	(4.69)**	(5.56)**
9-months				
	High	Returns	0.0027	-0.0002
		T-stat	(1.85)	(-0.08)
	Low	Returns	0.0065	0.0075
		T-stat	(5.28)**	(6.66)**
12-months				
	High	Returns	0.0030	0.0000
		T-stat	(2.71)**	(0.01)
	Low	Returns	0.0053	0.0064
		T-stat	(5.05)**	(6.24)**

* denotes significant at the 5% level

** denotes significant at the 1% level.