CHAPTER 1

Behavioural Finance and Momentum

ANDREW GRANT

1.1 INTRODUCTION

Behavioural finance aims to provide explanations for observed market phenomena outside the neo-classical view of financial markets. Proponents of efficient markets may argue that behaviourally biased traders will not affect prices in equilibrium, as they will make incorrect decisions and be driven out by rational arbitrageurs. Indeed, the 'no free lunch' or 'economic' approach to market efficiency suggests that, by and large, it should be difficult to profit from a simple trading strategy – such as momentum – without access to superior information. Under an alternative definition of market efficiency (e.g. Fama, 1970) asset prices should reflect fundamental value. A limits-to-arbitrage (Shleifer and Vishny, 1997) viewpoint contends that asset prices may not necessarily trade at fundamental levels because rational arbitrageurs face constraints that make it costly or risky to correct mispricing.

To provide an example, equity analysts play a crucial role in information production, and stocks without sufficient focus from market participants may not be correctly valued. Similarly, stocks with other trading frictions, such as low liquidity, high levels of idiosyncratic volatility, low levels of institutional investor ownership (making short-selling difficult) and high levels of valuation uncertainty (growth or technology stocks) are likely to experience stronger trading frictions. Indeed, much of the evidence shows that momentum is particularly prevalent among stocks that are subject to these trading frictions.

Other chapters in this book seek to explain momentum as a purely statistical phenomenon, for example, arising from autocorrelation, or statistical properties of sorted portfolios. In this chapter, we take a contrasting view, seeking to understand why the return processes may hold these properties to begin with. Behavioural finance helps provide insight into momentum returns by considering psychological explanations, including overreaction, underreaction, slow information diffusion, anchoring and sentiment. A common theme among these phenomena is that mispricing – or a temporary deviation from fundamental value – spurs momentum.

The approach taken in this chapter is not that momentum is solely driven by behavioural biases, but that a consideration of investor psychology may help to partially explain the prevalence of momentum profits or may be used to enhance the returns of a momentum strategy. A strict definition of what is categorised as 'behavioural finance' is not imposed, but I will consider issues that appear to be underpinned by either non-traditional investor preferences or beliefs, retail vs. institutional investors, or market-wide sentiment.

The behavioural approach mainly gained traction with the advent of the three-factor model of Fama and French (1996), and the noted inability of beta, firm size, and the value effect to explain short-term momentum returns. Following this, three highly influential models utilising various aspects of investor psychology were developed by Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999). These models have formed the basis for many empirical tests of momentum from the behavioural finance perspective. This chapter first examines the failure of risk-based explanations, then considers some of the predictions from the theoretical behavioural models, and then explores some empirical tests relating to these models.

One of the key insights of the Hong and Stein (1999) model is that slow information diffusion among market participants can lead to momentum. Empirical work by Hong, Lim and Stein (2000) has demonstrated momentum is particularly prevalent in small stocks, for example, supporting this notion. Chen and Lu (2017) use option markets, which are likely to be the choice of trading venue for informed traders, to infer the speed of information diffusion. They find that momentum is more pronounced in stocks that exhibit large changes in option implied volatility (where information is likely incorporated in the option but not stock market) exhibit stronger momentum than those that exhibit small changes in implied volatility.

The return pattern or price path taken by a stock, including large price movements – or an absence of large price movements – has also been shown to lead to continuation (momentum in returns), as investors may not efficiently impound information into stock prices. Recent evidence (Atilgan et al., 2020) suggests this is particularly an issue for downward price movements, where investors appear to underreact to potential risks of further price declines.

Closely related to momentum, the 52-Week High effect, as first documented by George and Hwang (2004), states that firms trading near the highest point over the previous year tend to continue upwards. Grinblatt and Han (2005) suggested that stocks near the 52-Week high are in the domain of gains for investors with prospect-theoretic preferences. Preference to sell winners (also known as the disposition effect) induces uninformed selling pressure by such investors, which consequently may lead to return continuation, supporting the contention of underreaction or delayed reaction driving momentum.

The issue of who 'creates' momentum can also be considered a behavioural issue. Unlike most other asset pricing anomalies, institutional investors appear to trade 'with' momentum strategies (Edelen, Ince and Kadlec, 2016). The counterparties, therefore are likely to be individual investors, selling out winners before price increases (as per the predictions of Grinblatt and Han, 2005), and similarly buying losers. While in the short-term, Kaniel, Saar and Titman (2008) argue that individuals are compensated for providing liquidity, at longer horizons, they tend to underperform institutional investors.

The final issue that is addressed in this chapter relates to investor sentiment. Recent attempts to operationalise behavioural finance have led to the construction of 'top-down' sentiment indices (e.g. Baker and Wurgler, 2006). The main idea of a sentiment index is to capture excessive mispricing (either over- or under-valuation), by combining factors such as IPO first-day returns that likely indicate excessive optimism or pessimism. Stocks that are difficult to value or difficult to arbitrage are most likely to load positively on a sentiment index. Momentum strategies appear to be mainly profitable during periods of high sentiment, but not during periods of low sentiment (e.g. Stambaugh, Yu and Yan, 2012; Antoniou, Doukas and Subrahmanyam, 2013). This is arguably driven by investor preferences but may also be driven by liquidity.

1.2 THE FAILURE OF RISK-BASED EXPLANATIONS

The inability to explain the returns to a momentum strategy was described as the 'prime embarrassment' of the three-factor model by Fama and French (1996, p. 75). After all, the value (High book-to-market value Minus Low book-to market value [HML]) factor in a three-factor model predicts that losing stocks will outperform winning stocks, consistent with long-term reversals but not with short-term momentum. Later, Carhart (1997) added the UMD (Up minus Down) factor to assess whether a portfolio's returns are consistent with those of a momentum strategy.

Other researchers have attempted to provide a risk-based explanation for momentum returns. Chordia and Shivakumar (2002), Cooper, Gutierrez and Hameed (2004) and Stivers and Sun (2010) all argue that momentum profits are strong during macroeconomic expansions but largely non-existent during recessions. Chapter 15 of this book discusses issues of momentum across the business cycle in more detail. Daniel and Moskowitz (2016) demonstrate that momentum performed particularly poorly during the recovery period from the financial crisis and argue that negative skewness in momentum returns (small positive returns most of the time, but occasional large crashes) is consistent with risk-based explanation. While I will not argue that these viewpoints are invalid, the fact that momentum has been a profitable trading strategy fairly consistently indicates that alternative (i.e. behavioural) explanations may be necessary to complete the picture.

1.3 BEHAVIOURAL MODELS OF MOMENTUM

Several key studies (e.g. Jegadeesh and Titman, 1993; Fama and French, 1996; Grundy and Martin, 2001; Griffin, Ji, and Martin, 2003) failed to find a satisfactory risk-based explanation for momentum profits, which led to the development of behavioural-based explanations. Three studies are considered seminal works in this area; Barberis et al. (1998, henceforth BSV), Daniel et al. (1998, henceforth DHS), and Hong and Stein (1999, henceforth HS). Each of these seeks to explain the existence of both momentum returns at a 6–12 month horizon, followed by the subsequent long-term reversals (as in DeBondt and Thaler, 1985). The seminal works of BSV, DHS and HS warrant a brief review. Many of the empirical studies of momentum have built upon components of one or more of the models.

While not specifically focused on momentum, the model of DeLong, Shleifer, Summers and Waldmann (1990) seeks to explain 'noise-trader risk' and why asset prices might deviate from fundamental values. They argue that the correlated trades of individuals, combined with constraints faced by institutional investors (either due to time horizons or risk aversion) means that stock prices can deviate from fundamental values for an extended period of time.

In short, informed arbitrageurs might understand that a stock is overvalued, but can be unwilling (or unable) to rectify the situation. Betting against sentiment-prone investors is costly (short-selling stocks is more expensive than buying stocks) and risky (it is difficult to tell when corrections to market prices will occur). These effects are exacerbated for hard-to-value stocks, or those that are particularly likely to be prone to sentiment-based mispricing.

It is from this background that Shleifer and Vishny (1997) developed the concept of 'limits to arbitrage'. Under this paradigm, stocks are generally priced at efficient levels, but may deviate from fundamental values based on the inability or unwillingness of arbitrageurs to correct the mispricing. The motivation for momentum from the behavioural finance perspective is that limits to arbitrage either cause overreaction or underreaction in prices. Disparity in information, combined with variations in transaction costs, may lead stocks away from fundamental value without immediate correction, leading to momentum opportunities.

In the BSV model, investors react to earnings surprises, with the belief that earnings are generated under one of two regimes. In the first regime, earnings are mean-reverting; a positive earnings surprise is likely to be followed by a negative earnings surprise and vice-versa. In the second regime, earnings move in a trend, a positive surprise is more likely to follow a positive surprise. The representative investor in the model uses Bayes' rule to update their beliefs about which earnings regime is in place. However, the investor exhibits tendencies of representativeness, leading them to reduce their reliance on probability laws in some circumstances, and conservatism, causing them to update their beliefs slowly in other situations. The result is underreaction to earnings surprises when investors believe earnings to be mean reverting, but a streak of positive or negative earnings has occurred. When the streak of consecutive earnings is broken by a change in sign, the representative investor overreacts, leading to large reversal.

The DHS model similarly produces momentum and reversals, but relies on a different structure to the BSV model. The representative investor is overconfident, meaning that they believe too strongly in the precision of their own private information. The investor also suffers from biased self-attribution, whereby they attribute too much significance to signals that confirm their prior belief – making them more overconfident – while downplaying or ignoring the impact of signals that contradict their prior belief.

The DHS model has two main features. The first relates to the price response function related to a private signal. If the signal is positive, informed investors immediately overreact and the security becomes overpriced. Because of biased self-attribution, the overpricing will be exacerbated with the arrival of public information thereafter. However, as public information continues to arrive, investors will see that their initial overconfidence was unjustified, leading to a correction phase. Thus, overconfidence drives momentum in the initial phase, and the longer-term reversal as investors are slow to realise their mistakes.

The second feature of the DHS model focuses on how the market responds to public or private information. In the model, investors may underreact to private information about a firm without the subsequent drift occurring. This would be the case when public information is known to all parties simultaneously. However, if there is a more gradual release of information (information either diffuses more slowly or is 'leaked' to some parties) then the underreaction by investors may result in price drift.

The HS model does not rely on specific behavioural elements, such as overconfidence or representativeness. It instead utilises the interaction between two groups of traders; 'newswatchers' who trade on the basis of public information (without worrying about past prices) and 'technical analysts' who trade on the basis of trends without consideration of fundamental values. Crucially to the model, newswatchers base their trades on information that diffuses slowly through the trading population. This leads to underreaction by newswatchers to fundamental information, which subsequently drives price drift. This drift is noticed by technical analysts who then follow the trend and push prices even further in their initial direction, leading to overpricing. Newswatchers re-enter the market to correct the overpricing, leading to a cycle of overreaction and reversals.

Shefrin (2008) argues that there are issues with each of these models. For example, both the BSV and DHS models seek to explain returns to the cross-section of stocks, yet feature only one security. In the HS model, newswatchers are inconsistent in how they develop trading plans. They trade with technical analysts on the upward-moving phase, and again on the downward-moving phase. Under the DHS model, investors overreact to private (rather than public) information, although Odean (1998b) argues that investors are more likely, in practice, to overreact to salient, attention-grabbing events. Similarly, the momentum build-up arises in the DHS model from an investor purchasing additional amounts of shares they already hold, as public information confirms the results of an investor's private signal. However, Odean (1999) finds, to the contrary, that investors prefer to purchase additional amounts of stocks that have declined, rather than increased, in price. In fact, due to the disposition effect (Shefrin and Statman, 1985), investors prefer to sell winning stocks and hold on to losers.

1.4 SLOW INFORMATION DIFFUSION

A critical aspect of the theoretical studies is that information diffuses slowly throughout the economy, at least to some participants. This may come from erroneous adjustments of beliefs (in the case of the BSV model, due to representativeness or conservatism) or through different reactions to public and private information (in the case of the DHS model).

Empirically, Hong et al. (2000) sorted stocks in terms of the expected speed of information diffusion. Using both firm size and analyst coverage as proxies, they find that momentum profits are, in fact, stronger in smaller stocks (excluding the very smallest size quintile, where liquidity issues dominate) and stocks with lower analyst coverage. In the tercile of stocks with the lowest expected analyst coverage (i.e. analyst coverage adjusted for firm size), momentum profits are 60% greater than for the tercile of stocks with high expected analyst coverage. Moreover, the effect of analyst coverage appears to be most pronounced in losing stocks; low-coverage stocks 'seem to react more sluggishly to bad news' (Hong et al., 2000, p. 268). The authors postulate that this is because, in the absence of outside analyst coverage, managers have the incentive to disseminate positive news (through increased disclosures) but not to broadcast negative news. Analyst coverage appears to help extract negative news from management.

A more recent theoretical contribution to the literature by Andrei and Cujean (2017) explores the role of information diffusion in generating patterns of momentum and reversal. Using a (non-behavioural) rational expectations framework, Andrei and Cujean (2017) derive an information arrival 'shape' that is necessary for momentum to arise, namely that private information must flow at an increasing rate. Using 'word-of-mouth' communication as an example, the authors demonstrate that it is possible for returns to continue (and subsequently reverse), even if traders are rational and risk-averse, and not subject to behavioural biases.

Chen and Lu (2017) use options markets to dynamically examine the speed of information diffusion in stocks. The logic is as follows: informed traders may prefer to use option rather than stock markets for reasons such as leverage or short sales constraints. Thus, for stocks with slow information diffusion, some traders will prefer to trade in the options markets to realise superior information. The authors utilise the information in options markets to identify those stocks with information yet to be incorporated into prices. Specifically, for winner stocks, if we also observe an increase in the price of call options, informed options traders believe that there is information to be impounded into the price. The same logic applies to loser stocks: informed option traders can sell call options if they think that the negative information associated with those loser stocks has not been fully incorporated in the stock prices.

Chen and Lu (2017) implement an enhanced momentum strategy based on information diffusion speed, taking a long position in winners with the largest growth in call option implied volatility, and shorting loser stocks with the largest drop in call option volatility. The strategy generates a return of 1.78% per month over the 1996–2011 period, whereas the return to a standard momentum strategy earned around 0.80% per month over the same period.

1.5 PATTERNS IN INFORMATION ARRIVAL

A recent strand of literature focuses on the type of information arrival that leads to underreaction or overreaction by investors. Following a large price change, for example, investors may need to drastically update their beliefs regarding expected future realisations of the stock. Cognitive psychology, from which much of behavioural finance is based, demonstrates that individuals are inefficient at updating probabilistic beliefs in response to new information (e.g. Camerer, 1987; Hogarth and Einhorn, 1992). Numerous experiments conducted by (among others) Tversky and Kahneman (1982) demonstrate that relative to the correct 'Bayesian' updating of beliefs, individuals tend to neglect or underweight the base-rate (prior probability) and overweight the new information (likelihood). This effect is systematic, and in aggregate implies that there would be an overreaction to large price movements, and underreaction to small price movements.

Consistent with the base-rate neglect hypothesis, Da, Gurun and Warachka (2014) argue that momentum arises because investors underreact to information arriving in small bits much like the proverbial 'frog in a pan' that does not notice as the water is slowly brought to boil. Da et al. (2014) show that stocks where past returns accumulate gradually exhibit more momentum than stocks where returns are accumulated in a lumpy fashion.

Savor (2012), following related work by Pritamani and Singal (2001) and Chan (2003), compares the price reaction to major price movements that are likely information-driven or non-information driven (a liquidity or sentiment shock, for example) where an accompanying analyst report is used as a proxy for information. Savor (2012) finds that information-driven price events are followed by a continuation in returns and non-information driven price events are followed by reversals. He argues that investors underreact to news about fundamentals but overreact to other shocks.

Chen, Yu and Wang (2018) examine the 'acceleration' of momentum profits, where the acceleration measure is calculated by regressing previous daily prices during the formation period on an ordinal time variable and the square of the ordinal time variable for each stock. The coefficient of the quadratic term ('convexity') measures the level of acceleration of returns. The authors find that buying winners with positive convexity (where returns are 'speeding up' during the formation period) and selling losers with negative convexity (accelerating downwards) outperforms a standard momentum strategy by 51.5% (0.95% per month vs. 0.63% per month). The authors attribute the performance differential to naïve extrapolation and also present an overreaction explanation.

Jiang and Zhu (2017) explore whether the market underreacts to large, discontinuous price movements ('jumps'). Using jumps in stock prices as a proxy for large information shocks, the authors provide evidence consistent with short-term underreaction in the US equity market. Jiang and Zhu construct a metric based on cumulative jump returns, and sorting on this they find that a strategy that takes a long position stocks with positive lagged (one- or three-month) jump returns and a short position in stocks with negative lagged jump returns earns significantly positive returns over the next one to three months.

In a thorough study, Atilgan et al. (2020) demonstrate that there is a significant negative cross-sectional relationship between expected downside risk and stock returns. Using proxies including Value at Risk (VaR) and Expected Shortfall (ES), the authors argue that investors underestimate the persistence in downside risk, and hence overprice stocks that have exhibited large recent losses. A value-weighted portfolio that takes a long position in stocks with low VaR and short in stocks with high VaR earns a one-month return of 0.78% per month in US equities over the period from 1962–2014. This return is not explained by a Fama-French five-factor model, nor illiquidity, coskewness or downside beta factors. Instead, it appears to be (i) most pronounced in stocks with low institutional ownership, suggesting a relationship with limits to arbitrage, (ii) in stocks with high retail investor participation and subject to low investor attention, and (iii) present and persistent across countries over the period 1988 to 2014. Atilgan et al. (2020) suggest that, unlike with upward movements, 'the elusive nature of left-tail risk makes the investors' attention constraints more likely to be binding', and argue that negative price shocks are harder to interpret by average investors.

1.6 THE 52-WEEK HIGH AND CAPITAL GAINS OVERHANG

The price path taken by a stock may also influence the speed of reaction to news. Some investors prefer to sell stocks that have increased in value from a reference point, such as the purchase price. This tendency, known as the disposition effect (Odean, 1998a), leads to an increase in the frequency of non-informational sales, as investors prefer to realise gains, rather than losses.

The 52-week high, a salient figure from both financial press and brokerage information, is a statistic showing the highest price a stock has traded at in the past year. Investors may compare the current stock price to the 52-week high and decide that the 52-week high represents a useful signal to sell, perhaps as they are anchored to the 52-week high. As an investor who is holding a stock near the 52-week high is also likely in the domain of gains, both biases work together to dampen the impact of good news on stocks near the 52-week high.

The examination of the 52-week high effect by George and Hwang (2004) demonstrates this point, finding that stocks trading close to the 52-week high exhibit returns of a similar magnitude to those of the classical Jegadeesh and Titman (1993) momentum strategies. George and Hwang (2004) demonstrate that the components of portfolios selected using the standard momentum approach differs from that of the 52-week high approach, thus the 52-week high effect does not strictly replicate the effect of constructing momentum profits based on past returns.

Future work has sought to shed light on the 52-week high effect. For example, Bhootra and Hur (2013) construct a related measure called 'recency rate', indicating the number of days since a stock has been at its 52-week high. Stocks that have recently been at their 52-week high tend to outperform stocks that have been at their 52-week highs in the distant past, by approximately 0.70% per month. Moreover, a strategy combining 'nearness' and 'recency' to the 52-week high outperforms one examining nearness alone, suggesting that the effects work in combination.

The 52-week high effect is closely related to the 'capital gains overhang' (CGO) effect described in Grinblatt and Han (2005). To explain CGO, suppose that, in aggregate, investors hold prospect theory preferences, and, due to mental accounting, they separate winning stocks from losing stocks based on price changes from a reference price (typically chosen as the purchase price). Under prospect theory, investors are risk-averse in the domain of winners and risk-seeking in the domain of losses, which leads them to prefer to sell winners and hold onto losers. Grinblatt and Han (2005) argue that momentum arises from the systematic preference by investors to sell winners over losers, which impedes price movements to fundamental values. Consider, for instance, a stock in the domain of gains. As investors rush to lock in gains based on price increases from the purchase price – a non-informational reason – it delays the shift upwards to fundamental value. In the domain of losses, a reluctance to sell losing stocks can delay the impounding of information into stock prices, leading to a downward continuation.

The key measure constructed by Grinblatt and Han (2005), the CGO, is constructed using an estimate of the mean reference price distribution. The mean of the reference point distribution is estimated as the weighted moving average of past prices, with weights determined by turnover rates. The weight associated with a given price is the turnover rate probability that a share was last purchased a particular past date, and has not been traded since that time. Thus, 'winners' will have a current price exceeding the reference price, and 'losers' will have a current price below the reference price. The percentage difference between the current price, and the reference point is defined as the capital gains overhang, so winners exhibit positive CGO, and losers exhibit negative CGO. Weighting the reference price by past turnover rates means that actively traded stocks tend to exhibit lower absolute levels of CGO, as more recent prices exhibit a higher weight in the calculation of the reference point.

In a study of common shares traded on the NYSE and AMEX exchanges between 1962 and 1996 (with NASDAQ firms excluded because of the dealer structure) Grinblatt and Han (2005) regress the week t return of stock k on past cumulative returns (1 month, 12 months and 36 months), market capitalisation, average weekly turnover and the capital gains overhang. They find that the inclusion of CGO as an explanatory variable renders the 12-month past return insignificant, suggesting that momentum is broadly driven by the tendency of investors to realise gains rather than losses.

One of the advantages of the CGO metric, compared with other measures requiring the use of reference prices is that it simply employs past price and volume data in its construction. Other studies of individual investor behaviour (e.g. Odean, 1998a; Feng and Seasholes, 2005) examine whether investors prefer to realise gains rather than losses relative to some reference point (usually taken as the purchase price). Of course, the actual reference price (or price that investors internally use to decide whether they are in the domain of gains or losses) used by investors cannot be determined. Moreover, whether investors prefer to purely seek gains or losses without regard to their size is debatable (Ben-David and Hirshleifer, 2012), and the CGO may provide a more robust measure of aggregate profit-taking trade motivations.

Some other studies have used the principles of Grinblatt and Han's (2005) CGO with further refinements to test asset pricing implications. For example, Goetzmann and Massa (2008) examine whether the proportion of disposition-prone investors holding a stock dampens returns and volatility. They find that the disposition effect is not only present at the stock level, but aggregates to the market level, creating a common factor that disperses stock returns.

Hur, Pritamani and Sharma (2010), in order to refine the CGO metric, weigh past prices by the proportion of share turnover that is attributable to individual investors. Even though they use a proxy metric, such as the proportion of shares not owned by institutions (residual institutional ownership), or the proportion of trades in a stock below $10,000 dollars (e.g. Hvidkjaer, 2008; Barber, Odean and Zhu, 2009), to identify turnover due to individuals, they find that a CGO-momentum trading strategy can be enhanced by focusing on stocks with a higher level of individual trading activity. In a (6, 1, 6) momentum strategy, for instance, in their sample of US stocks from 1980 to

2005, Hur et al. (2010) find that winners with high individual presence (based on CGO measures constructed from residual institutional ownership) outperform winners with low individual presence by 0.206% per month. Across the same time frame, losers with low individual presence underperform losers with high individual presence by 0.351% per month. The general result taken from Hur et al. (2010) is that CGO measures constructed based on residual institutional ownership appear to identify persistent losers, while CGO measures constructed using small-trade turnover help identify persistent winners.

Hur and Singh (2019) further investigate the relationship between capital gains overhang and the anchoring effect of the 52-week high. While they represent similar behaviour from individuals, Hur and Singh (2019) note that the realisation of capital gains is an effect driven by existing shareholders, while the 52-week high is relevant also to prospective shareholders. The two effects appear to be complementary; in their empirical study covering US stocks over the period 1963 to 2013, Hur and Singh (2019) find that there is a correlation of 0.56 between the two measures. The authors perform double sorts (into terciles) on the CGO and 52-week high measures, finding that stocks with high levels of capital gains overhang and close to the 52-week high return earn an average of 1.07% per month (in the six months following portfolio formation) more than stocks with low levels of CGO and far from the 52-week high. This compares favourably with decile-sorted portfolios of the 52-week high alone (which earn around 0.82% per month) but similarly to stocks sorted on CGO (which earn around 1.10% per month). In further tests, the authors find that the strategy can be enhanced by considering portfolios with high residual institutional investor ownership, low analyst coverage and high levels of illiquidity.

1.7 INSTITUTIONAL TRADING AND MOMENTUM PROFITS

Edelen et al. (2016) explore the role of institutional investors in contributing to stock market anomalies. They argue that institutions tend to make trades against the prescribed direction of most anomalies, doing so because institutional investors would prefer to hold stocks of ‘good companies’ with the aim of outperforming a benchmark. As it is the overvalued (i.e. the prescribed short leg) of most anomaly portfolios that institutions buy, the authors argue that institutions are not sophisticated arbitrageurs (contrary to Shleifer and Vishny’s [1997] limits to arbitrage theory). Rather, they appear to be affected by institutional constraints, or agency biases.

For example, institutions prefer to load up on growth (low book-to-market) rather than value (high book-to-market) stocks and fail to earn the value premium. Only two of the anomalies of the seven they consider (gross profitability and momentum) lead to institutions increasing their holdings in the long-leg portfolio (winner stocks in the case of momentum). Thus, institutions actually contribute to the existence of momentum profits by purchasing recent winners, leading to continued upwards drift.

Vayanos and Woolley (2013) build a theoretical model in which momentum arises as a consequence of delegated portfolio management. Their argument is as follows.

Suppose that a negative shock hits the fundamental value of some assets. Investment funds holding these assets realise low returns, triggering outflows by investors who update negatively about the efficiency of the managers running these funds. As a consequence of the outflows, funds sell assets they own, and this further depresses the prices of the assets hit by the original shock. Momentum arises if the outflows are gradual, and if they trigger a gradual price decline and a drop in expected returns. Reversal arises because outflows push prices below fundamental values, and so expected returns eventually rise.

Baltzer, Jank and Smajlbegovic (2019) examine a unique data set (covering the period 2005–2012) from the German centralised registry (the Securities Holding Statistics, SHS), which reports trades made by all financial institutions and their customers at the quarterly level. Customers' securities holdings are further broken down by investor sector and customer nationality. The authors form winner and loser portfolios (top and bottom 30% of stocks based on the prior four-quarter performance), with a one-month holding period. A momentum strategy works well in Germany over the time period covered.

Examining ownership changes over the holding period, it is found that foreign investors (who are mainly institutions) tend to be momentum traders (similar to the result found in Grinblatt and Keloharju's [2000] study of Finnish investors), mainly through their sales of losing stocks than purchasing winners. Mutual funds are also momentum traders, but to a lower extent.

Domestic households, therefore, tend to be the counterparty to these trades, with a tendency to act as contrarian investors, buying losers and selling winners. Household contrarian trading has been demonstrated in a number of other studies, although typically at shorter horizons. Perhaps the most well-known example is from Kaniel et al. (2008), who demonstrate that individuals earn short-term (one month) returns from providing liquidity by selling to institutional investors. Barrot, Kaniel and Sraer (2016) demonstrate, using a large sample of French investors, that individuals are contrarians at the daily, weekly, and monthly horizons. Due to their holding periods, they argue that individuals do not actually earn the liquidity premiums from Kaniel et al. (2008), as the profits reverse after two months, and individuals tend to have longer holding periods.

1.8 SENTIMENT AND MOMENTUM

Sentiment, as broadly defined in the behavioural finance literature, is any non-fundamental factor that affects asset prices. Baker and Stein (2004) note that, if it is cheaper to open long positions than to enter into a short position, as it is in practice, the willingness of individual investors to trade represents a form of sentiment. Overconfidence, as in the DHS model, leads biased investors to over-weight their own private signal of security values. In the presence of short-sales constraints, such investors are willing to purchase, but not short stocks. In Baker and Stein's (2004) model, therefore, liquidity provides a measure of investor sentiment. Empirically, Baker and Stein (2004) find low future returns follow shocks to a turnover-based measure of liquidity, supporting the case.

Baker and Wurgler (2006), explaining that sentiment is difficult to measure, construct an index of investor sentiment, based on principal components analysis on proxy measures of optimism and pessimism, such as the average first-day returns on IPOs, and the share of equity issuance over total security issuance. Baker and Wurgler (2006) demonstrate that small, young, currently unprofitable, potentially profitable stocks, with high value uncertainty (such as an internet start-up in the dot-com bubble of the late 1990s) are particularly prone to sentiment risk. By definition, sentiment is mean-reverting, and so such stocks are overpriced in periods of high market-wide sentiment and under-priced in periods of low sentiment.

The linkage between sentiment and momentum was first discussed in Antoniou et al. (2013). Using a fundamental adjusted version of the Michigan Consumer Sentiment Index as a proxy for market-wide sentiment, Antoniou et al. (2013) find that momentum profits are only reliably positive in periods of high sentiment. The authors argue that, due to cognitive dissonance, losing stocks continue to underperform in periods of high-sentiment as investors pay less attention to the disappointing performance of losing stocks in overly optimistic periods. In US equities over the period 1967–2008, they find that a (6, 1, 6) momentum strategy earns a significant monthly return of 2.00% following optimistic periods, and an insignificant 0.34% per month following pessimistic periods. The sentiment momentum effects appear stronger for small capitalisation stocks, suggesting that the influence of sentiment is more pronounced in smaller companies that are harder to value and hence more prone to subjective evaluations. Further analysis of order flow in Antoniou et al. (2013) shows that small investors are slow to sell losers during optimistic periods, which prolongs the pricing of bad news, and supports the argument of cognitive dissonance.

Stambaugh et al. (2012) argue that overpricing (due to short-sales constraints) is more prevalent than underpricing, and demonstrate that several anomalies, including momentum, are profitable following periods of high sentiment. Stambaugh et al. (2012) show that the short leg of momentum earns significantly negative returns of −1.24% per month following periods of high sentiment (where 'high' sentiment is above the median level of Baker and Wurgler [2006]) in US equities over the period 1965–2007. However, the short-leg returns (positive) 0.34% per month following periods of low sentiment. Overall, they find that momentum is nearly twice as profitable following periods of high sentiment (2.03% per month) against low sentiment (1.09% per month).

1.9 DISCUSSION

Momentum has proven to be a profitable strategy, for the most part, for an extended period of time. Investor psychology has been used to explain a portion of the persistence of the phenomenon in the presence of seemingly efficient markets.

From the evidence presented in this chapter, the speed of information diffusion plays a key role in prices deviating from fundamental values, which is when momentum appears to arise. The reasons that information diffuses slowly may not be entirely driven by investor sentiment or behavioural biases. It does, however, seem likely that incorporating features such as individual investor trading around price anchors such as the 52-week high, the level of a sentiment index or the path taken by a stock to achieve its status as a winner or loser can help to enhance a momentum strategy.

As markets continue to evolve, some of the behavioural biases of individuals in equity trading may be attenuated. For example, with a larger focus on passive trading through ETFs (exchange traded funds), some of the noise is likely to be removed from individual stocks. Information may diffuse more quickly, and momentum may become more of a short-term strategy. Specifically, it should be possible to use the behavioural information discussed in this chapter by adjusting the magnitude of the formation period in a dynamic fashion.

REFERENCES

Andrei, D. and Cujean, J. 2017. Information percolation, momentum, and reversal, *Journal of Financial Economics*, **123**, 617–645.

Antoniou, C., Doukas, J.A., and Subrahmanyam, A. 2013. Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, **48**, 245–275.

Atilgan, Y., Bali, T.G., Demirtas, K.O., and Gunaydin, A.D. 2020. Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics*, **135**(3), 725–753.

Baker, M. and Stein, J. C. 2004. Market liquidity as a sentiment indicator. *Journal of Financial Markets*, **7**, 271–299.

Baker, M. and Wurgler, J. 2006. Investor sentiment and the cross-section of stock returns. *Journal of Finance*, **61**, 1645–1680.

Baltzer, M., Jank, S., and Smajlbegovic, E. 2019. Who makes momentum? *Journal of Financial Markets*, **42**, 56–74.

Barber, B.M., Odean, T., and Zhu, N. 2009. Do retail trades move markets? *Review of Financial Studies*, **22**, 151–186.

Barberis, N., Shleifer, A., and Vishny, R. 1998. A model of investor sentiment. *Journal of Financial Economics*, **49**, 307–43

Barrot, J.-N., Kaniel, R., and Sraer, D. 2016. Are retail traders compensated for providing liquidity? *Journal of Financial Economics*, **120**, 146–168.

Ben-David, I. and Hirshleifer, D. 2012. Are investors really reluctant to realize their losses? Trading responses to past returns and the disposition effect. *Review of Financial Studies*, **25**, 2485–2532.

Bhootra, A. and Hur, J. 2013. The timing of 52-week high price and momentum. *Journal of Banking and Finance*, **37**, 3773–3782

Camerer, C.F. 1987. Do biases in probability judgments matter in markets? Experimental evidence. *American Economic Review*, **77**, 981–997.

Carhart, M.M. 1997. On persistence in mutual fund returns, *Journal of Finance*, **52**, 57–82.

Chan, W.S. 2003. Stock price reaction to news and no-news: Drift and reversal after headlines. *Journal of Financial Economics*, **70**, 223–260.

Chen, L.-W., Yu, H.-S., and Wang, W.-K. 2018. Evolution of historical prices in momentum investing. *Journal of Financial Markets*, **37**, 120–135.

Chen, Z. and Lu, A. 2017. Slow diffusion of information and price momentum in stocks: Evidence from options markets. *Journal of Banking and Finance*, **75**, 98–108.

Chordia, T. and Shivakumar, L. 2002. Momentum, business cycle and time-varying expected returns. *Journal of Finance*, **57**, 985–1019.

Cooper, M., Gutierrez, R., and Hameed, A. 2004. Market states and momentum. *Journal of Finance*, **59**, 1345–1365

Da, Z., Gurun, U., and Warachka, M. 2014. Frog in the pan: continuous information and momentum. *Review of Financial Studies*, **27**, 2171–2218.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. 1998. Investor psychology and security market under and overreactions. *Journal of Finance*, **53**, 1839–86.

Daniel, K. and Moskowitz, T.J. 2016. Momentum crashes. *Journal of Financial Economics*, **122**, 221–247.

DeBondt, W.F.M. and Thaler, R.H. 1985. Does the stock market overreact? *Journal of Finance*, **40**, 793–805.

DeLong, J.B., Shleifer, A., Summers, L.H. and Waldmann R.J. 1990. Noise trader risk in financial markets, *Journal of Political Economy*, **98**, 703–738.

Edelen, R.M., Ince, O.S. and Kadlec, G.B. 2016. Institutional investors and stock return anomalies, *Journal of Financial Economics*, **119**, 472–488.

Fama, E.F. 1970. Efficient capital markets: A review of theory and empirical work. *Journal of Finance*, **25**, 383–417.

Fama, E. and French, K. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Financial Economics*, **51**, 55–84.

Feng, L. and Seasholes, M.S. 2005. Do investor sophistication and trading experience eliminate behavioral biases in financial markets? *Review of Finance*, **9**, 305–351.

George, T.J. and Hwang, C.-Y. 2004. The 52-week high and momentum investing. *Journal of Finance*, **59**, 2145–2176.

Goetzmann, W.M. and Massa, M. 2008. Disposition matters: Volume, volatility, and the price impact of a behavioral bias. *Journal of Portfolio Management*, **34**, 103–125.

Griffin, J.M., Ji, X., and Martin, J.S. 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *Journal of Finance*, **58**, 2515–2547.

Grinblatt, M. and Han, B. 2005. Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, **78**, 311–339.

Grinblatt, M. and Keloharju, M. 2000. The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of Financial Economics*, **55**, 43–67.

Grundy, B.D. and Martin, J.S. 2001. Understanding the nature of risks and the sources of rewards to momentum investing. *Review of Financial Studies*, **14**, 29–78.

Hogarth, R.M. and Einhorn, H.J. 1992. Order effects in belief updating: The belief-adjustment model. *Cognitive Psychology*, **24**, 1–55.

Hong, H., Lim, T., and Stein, J.C. 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance*, **55**, 265–295.

Hong, H. and Stein, J. 1999. A unified theory of underreaction, momentum trading and overreaction in asset markets. *Journal of Finance*, **54**, 2143–2184.

Hur, J., Pritamani, M., and Sharma, V. 2010. Momentum and the disposition effect: The role of individual investors. *Financial Management*, **39**, 1155–1176.

Hur, J. and Singh, V. 2019. How do disposition effect and anchoring bias interact to impact momentum in stock returns? *Journal of Empirical Finance*, **53**, 238–256.

Hvidkjaer, S. 2008. Small trades and the cross-section of stock returns. *Review of Financial Studies*, **21**, 1123–1151.

Jegadeesh, N. and Titman, S. 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, **48**, 65–91.

Jiang, G.J. and Zhu, K.X. 2017. Information shocks and short-term market underreaction. *Journal of Financial Economics*, **124**, 43–64.

Kaniel, R., Saar, G., and Titman, S. 2008. Individual investor trading and stock returns. *Journal of Finance*, **63**, 273–310.

Odean, T. 1998a. Are investors reluctant to realize their losses? *Journal of Finance*, **53**, 1775–1798.

Odean, T. 1998b. Volume, volatility, price and profit when all traders are above average. *Journal of Finance*, **53**, 1887–1934.

Odean, T. 1999. Do investors trade too much? *American Economic Review*, **89**, 1279–1298.

Pritamani, M. and Singal, V. 2001. Return predictability following large price changes and information releases. *Journal of Banking and Finance*, **25**, 631–656.
Savor, P.G. 2012. Stock returns after major price shocks: The impact of information. *Journal of Financial Economics*, **106**, 635–659.
Shefrin, H. 2008. *A Behavioral Approach to Asset Pricing* (2e), Amsterdam: Elsevier.
Shefrin, H. and Statman, M. 1985. The disposition to sell winners too soon and ride losers too long: Theory and evidence. *Journal of Finance*, **40**, 777–790.
Stambaugh, R.F., Yu, J., and Yuan, Y. 2012. The short of it: Investor sentiment and anomalies. *Journal of Financial Economics*, **104**, 288–302.
Shleifer, A. and Vishny, R.W. 1997. The limits of arbitrage. *Journal of Finance*, **52**, 35–55.
Stivers, C. and Sun, L. 2010. Cross-sectional return dispersion and time-variation in value and momentum premia. *Journal of Financial and Quantitative Analysis*, **45**, 987–1014
Tversky A. and Kahneman D. 1982. Evidential impact of base-rates. In: Kahneman, D., Slovic, P., and Tversky, A., editors. *Judgment under Uncertainty: Heuristics and Biases*. Cambridge: Cambridge University Press, 153–160.
Vayanos, D. and Woolley, P. 2013. An institutional theory of momentum and reversal. *Review of Financial Studies*, **26**, 1087–1145.