Taming the Animal Spirits: Predicting Psychologically Based Stock Price Movements

Robert East (✉ R.East@kingston.ac.uk)
Kingston University
Malcolm Wright
Massey University

Research Article

Keywords: Momentum, Stock Price Prediction, Artificial Intelligence, Availability, Negativity Bias, Information diffusion

Posted Date: September 27th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-2090235/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License
Abstract

This paper is concerned with the psychological and social factors that may be used in the prediction of stock prices using artificial intelligence (AI). Examples of price movements that appear to be affected by such factors are drawn from market behavior during the Covid-19 pandemic. A review of the main effects attributable to psychological mechanisms follows: the disposition effect, momentum, and the response to information. These effects are explained by reference to regression to the mean, negativity bias, the availability mechanism, and information diffusion. Drawing on the consumer behaviour literature, we identify factors that are likely to indicate psychologically based price effects and suggest two new measures: changes in the proportion of new investors and the volume of publicity/word of mouth in relation to a firm's capitalization.

Introduction

The prediction of stock prices is increasingly dependent on artificial intelligence (AI) (e.g. Baldwin 2019, Rosenbaum 2017). Shanmuganathan (2020) reports a rise in AI managed wealth from 300 million dollars in 2014 to an estimated 2 trillion in 2020. Recent successes in fields as varied as the structure of proteins and winning in the game Go show the potential of AI (Callaway 2020, Koch 2016). AI analysis requires large volumes of relevant data; here, there is no shortage of market data, company statistics, and data on the economy, which can be used to establish whether a stock is underpriced or overpriced, and by how much, according to fundamental criteria. However, sometimes prices rise or fall in a manner that cannot easily be justified from a financial standpoint. These changes appear to rest on exaggerated beliefs about what will happen to the firm's profits and thus depend, in part, on individual and social psychological mechanisms rather than financial analysis. In principle, AI should be able to predict price movements based on these psychological mechanisms, but such predictions require the input of appropriate data. This paper is concerned with the nature of such data. The main part of the paper begins with a description of stock price movements over the first part of the Covid-19 pandemic that seemed difficult to explain using financial criteria; these provide examples of psychologically based stock price movements. Following this, the main psychological mechanisms that appear to affect stock prices are identified. Then, these are used to explain the pandemic price movements. Finally, an assessment is made of the data that could help in an AI prediction of psychologically based price movements. Here, we draw on methods and evidence that have been found useful in the prediction of consumer brand purchase. Our purpose is to identify predictive factors which may have been neglected by those who focus on stock fundamentals.

Estimates vary but it appears that around 60 percent of US stock market trades are computer driven and based on algorithms. High-frequency trades of this type benefit from speed of transaction and are intended to make small gains by capitalizing on arbitrage, statistical effects, and minor inefficiencies in markets. Such trades are held for less than a minute on average and so, despite their high volume, this use of the market employs only a small proportion of the total capital involved in stock investment. Because of this, these trades do not normally have much impact on market price levels. A much larger
weight of investment rests on the Warren Buffet approach. Here investing is based on financial fundamentals, company management and history, and market prospects; often, stocks are held for years. There is some debate on what factors are fundamental and there seems to be a case for including softer variables; for example, Gupta, Lehmann and Stuart (2004) point to the importance of intangible assets and find that customer retention is a major correlate of stock market value. A third approach to investment, technical analysis, uses statistical techniques and AI to predict market prices. Usually, this is applied to predictions of the market a few days ahead, using market data and leading indicators; this approach can claim some success (e.g. Zheng and Jin 2017).

This paper is also concerned with the use of AI but focuses on the social and psychological propensities of investors that affect stock prices. These propensities may cause price trends to become exaggerated and outrun the value of the stock when this is assessed on fundamentals. Keynes (1936) coined the term ‘animal spirits’ to describe such investor motivation which may raise the price of a stock above its fundamental value or, when negative, may cause a stock to be undervalued. These effects can be observed over periods ranging from weeks to years and provide advantage to investors following the Warren Buffet approach, who may be able to buy stocks that are fundamentally underpriced and avoid stocks that are overpriced. However, such investors may miss gains from buying a rising stock, or short selling a falling stock, when a further price rise/fall is predictable from psychological mechanisms. There will also be occasions when a stock is both fundamentally underpriced and the subject of excessive investor enthusiasm, which amplifies the scope for gain. Similarly, stocks may be assessed as poor value and also subject to extra investor distain, which raises the scope for short selling. Trading on the basis of psychological factors may tend to increase price swings and, perhaps because of this, is often described disparagingly as speculation, but it is a legal activity, and we should seek to understand when and how such trades bring returns.

Although psychologically based biases are clearly demonstrable, at least in retrospect, they take place over time and are likely to differ in degree and duration with the condition of the market, the type of company, and the publicity accompanying the factors affecting prices. These complications make the prediction of psychologically based movements of price difficult, and the purpose of this paper is to suggest factors that might improve such prediction. AI-based stock assessment, which incorporates evidence relating to investor bias, should be able to improve on human judgment and reduce the need for human stock picking. AI analysis can call upon substantial amounts of financial data but would benefit from measures of factors that relate to investor psychology if these can be identified.

Fama (1970), argued that stock markets are efficient in the sense that stock prices immediately reflect all available relevant information. This would mean that there is no point in basing investment on public information because the advantage that this confers would already have been consolidated in the stock price. However, there is evidence that biases occur and persist. For example, Dimson, Marsh and Staunton (2002) found that over 101 years ‘value’ stocks, which trade at relatively low prices relative to book value, were regularly underpriced in 13 out of 14 countries since yields from these stocks were on average, substantially larger than yields on growth stocks. It is rational to buy such underpriced value stocks but
investors do not do so in sufficient numbers to raise their prices. It is now clear that there are psychologically based biases that move stock prices and other market judgments away from valuations based on fundamentals. For example, Lee, O’Brien and Sivaramakrishnan (2010) show that market forecasts are biased toward current trading conditions; this reduces forecast accuracy and impairs the efficiency of capital allocation. Once this bias is measured, forecasts can be adjusted to take account of it. If the prediction of future stock prices can be improved, stock traders may benefit and the efficiency of markets may be enhanced.

This paper now turns to some evidence of stock price movements that appear to be based on psychological factors; we describe odd price movements during the earlier part of the Covid-19 pandemic. Then, attention is given to clarifying and organizing the psychological processes that appear to be behind such stock price movements. In this review, studies relating to three important issues in behavioral finance are examined, the disposition effect, the momentum effect, and the use of information by investors, with a focus on explaining the processes involved. These explanations are used to interpret the odd stock price effects that were observed during the pandemic. Finally, drawing on work in consumer behavior, a review is made of measures that could be relevant to predicting psychologically based price movements. This work is not definitive. The purpose is to identify likely explanations and therefore measures that could be relevant in AI analysis; the latter, when conducted, will test our proposals.

Stock Price Movements During The Covid-19 Pandemic

Previous pandemics, including the Spanish flu in 1918-9, did not have much effect on stock prices but, in these cases, there was no attempt by governments to curtail social and economic activity (Baker et al. 2020). In the Covid-19 pandemic, there was little stock price reaction to the outbreak in Wuhan for some time (Capelle-Blancard and Desroziers 2020). On February 4th, 2020, the Guardian commentator, Nils Pratley, noted that Western stock markets were disregarding the threat, and it was not until late February that stock prices started falling. With the advantage of hindsight, it seems extraordinary that the impact of the pandemic on cruise firms, airlines and hospitality was not anticipated until then. When the slide started, the Dow Jones Industrial Average lost 26 percent in four trading days (Mazur, Dang and Vega, 2020) but the full decline was extended over a month and there was massive volatility (Baker et al., 2020). The decline in prices shown by indexes such as the Dow and FTSE100 then reversed so that about half the losses were recovered over the next few months. Some individual company crashes have been similarly quick; for example, the fall in the BP stock price following the Deepwater Horizon disaster took about six weeks and was followed by some recovery. However, compared with the 1929 crash and the bursting of the dot-com bubble, the Covid crash was rapid. The 1929 crash occurred over three years and the dot-com bubble burst over two and a half years. Recovery after these crashes was also slower than that observed with Covid; in the case of the 1929 crash this took years and after the dot-com fall, the NASDAQ took 10 months to regain about 50 percent of the drop.

Firms that were directly impacted by pandemic restrictions fared worse. For example, the cruise firm, Carnival, lost about 90 percent of its stock value in the initial slide. So also did Cineworld and United
Airlines. But, like the main indexes, the stock price of these companies recovered part of the fall over the next few months.

One might expect the gainers from the pandemic such as Amazon, Asos (online clothing), Zoom and Ocado (grocery home delivery technology) to show a reverse pattern but here some price movements were peculiar. Initially, Amazon dipped a little and Asos lost two thirds of its value. It seems that investors had failed to grasp the fact that a lockdown was likely and that online firms would be at an advantage. After a few weeks, the stock price of these two firms began to rise along with other beneficiaries of the lockdown such as Zoom and Ocado. This rise in stock price of the winners took much longer than the fall of the whole market. Amazon's price started rising at the beginning of April 2020, and continued to rise until August when it plateaued at approximately double the pre-pandemic level. Similarly, Zoom climbed steadily to a fourfold increase in stock price by October and then fluctuated, Ocado more than doubled in value by the end of September. Market analysts have long recognized that markets usually fall rapidly and rise slowly; they suggest that, when owners of stocks have borrowed heavily against the value of their investments (high leverage), they may have to sell quickly to resolve their position when the price falls, thus accelerating the decline. However, a rising market allows investors to borrow more on margin, thus accentuating a boom. Leverage must play some part in price movements, but it seems likely that psychological processes were a major factor in the effects described here.

Reviewing this account, there are four features that require explanation and to which we shall return:

- the delay before prices fell
- the overshoot when stocks did fall
- the initial failure to recognize the advantage of online firms
- the slow rise of the winners

Disposition And Momentum Effects

The disposition effect is the tendency to sell a stock that has risen in preference to one that has fallen. People are risk averse with regard to gains and risk prone for losses; this is known as the reflection effect. The plot of psychological value (utility) on the y-axis is curved toward the x-axis measuring gain/loss. Thus, with each unit increase in objective value, the increment in utility diminishes and with each unit increase in objective loss, the increment in disutility diminishes. This diminishing marginal utility means that the chancy gain from keeping a winner has lower utility than the certain gain from selling it, which motivates selling. Correspondingly, the chancy loss from keeping a loser has lower disutility than the certain loss on sale, which motivates retention. Additionally, the disposition effect may be supported by a belief that price movements tend to reverse, and Fogel and Berry (2010) found more regret about selling a loser than a winner. Others, such as Shefrin and Statman (1985) have related the disposition effect to loss aversion but this explanation now seems to be in doubt.
The disposition effect is widely found. Shefrin and Statman noted a failure to cut losses by both professional traders and individual investors and, interestingly, Garvey and Murphy (2010) observed that institutional traders held losers proportionately longer than retail traders. The disposition effect also appears as an aggregate volume effect following price declines and rises (Lakonishok and Smidt 1986). Though the disposition effect is generally found, Lehenkari and Perttunen (2010) showed that, in a severe bear market, Finnish investors, while still averse to selling losers, were not prone to sell winners. One important effect of the disposition effect is that it tends to stabilize markets because it encourages selling in a rising market and retention of stocks in a falling market.

The disposition effect may lead to a loss. Odean (1998) found that investors lose an average of 3.4 percent in the following year by selling a winner in preference to a loser since there is a momentum effect with trends tending to continue for a while. Taking advantage of this effect, Jegadeesh and Titman (1993) found that buying stocks that have performed well, and selling stocks that have performed poorly, generated significant positive returns over three to twelve month holding periods. Dimson, Marsh and Staunton (2017) calculated the effect of a momentum strategy based on the performance of the top 100 UK stocks over one year and found a clear advantage. A review by O’Brien, Brailsford, and Gaunt, (2010) shows that momentum strategies over a period of 12 months generally shows a premium with the main gain from selling the losing stocks. But for longer periods, the outcome changes. De Bondt and Thaler (1985) found that investing in stocks that had underperformed brought a return that was 19.6 percent better than the market average after 36 months whereas a similar investment in outperforming stocks gave a return of 5 percent below the market average after 36 months. DeBondt and Thaler ascribed their findings to overreaction to information about stocks leading to excessively depressed prices in the case of underperforming stocks, and the reverse for outperforming stocks. If these prior movements in price were the result of the momentum effect, it seems that this effect carries rising/falling prices to a point above/below their long-run level. Consistent with DeBondt and Thaler’s evidence, Bohl, Czaja, and Kaufmann (2016) found that momentum strategies do poorly in highly volatile market recoveries because loser portfolios rebound from a very depressed state. Clearly, timing is key for those seeking to profit from momentum. In this context, it is difficult to identify stocks that are gathering momentum. Chen, Chou, and Hsieh (2017) found that more than 40 percent of winners and losers fall out of their respective groups in the month following group formation. However, when one more month of gain/loss was required for classifying the winners/losers, there was much stronger momentum persistence.

DeBondt and Thaler’s evidence indicates that underperforming stocks become more underpriced than outperforming stocks become overpriced; this suggests that negative information has more impact than positive information, an observation supported by Akhtar et al (2011) and Reyes (2019). When portfolios are constructed from the extremes of a distribution, some part of the subsequent change in portfolio valuation will result from regression to the mean since stocks with extreme valuations are likely to have these valuations in part because of high random error which will tend to return to an average level in a subsequent period. The effect of regression to the mean will be to reduce the gain in a portfolio of winners and increase the gain of a portfolio of losers. This could explain the differential performance of
winners and losers in DeBondt and Thaler’s study but another effect, negativity bias, may enhance the performance of the losers.

In explaining negativity bias, we need to recognize that information that is consistent with a receiver’s current evaluation of a stock may increase their certainty about its worth but is unlikely to much affect their evaluation. However, information that implies a value that is different from a receiver’s current evaluation will exert an influence toward the implied value. Some new information may be disregarded by investors but, when it cannot be discounted, the degree of influence should be a function of the magnitude of the gap between the value implied by the new information and the value previously held by the receiver. Thus, an investor’s subjective stock valuation will be affected more if new information is substantially at odds with his/her prior beliefs about the stock’s value. Most information is positive. For example, there is approximately three times as much positive word of mouth as negative (East, Hammond and Wright 2007), and Peterson and Wilson (1992) report data that indicate a ratio of satisfaction to dissatisfaction of the order of 10:1. This predominantly positive information shapes attitudes and makes the majority of these attitudes correspondingly positive. This means that negative information is more likely to be at odds with current thinking than positive information. As a result, negative information will have more effect on evaluation. For example, most people are viewed positively and, as a result, negative information on a person usually has more effect on judgments about that person than positive information (Fiske 1980). This is the main explanation for negativity bias but other ways in which negative information could have more effect are discussed by Rozin and Royzman (2001) and Skowronski and Carlston (1989).

Here, it is proposed that information about stocks is more often positive than negative and, correspondingly, people are normally positive about their investments. As a result, the impact of negative information on a stock will depress the price more than positive information will uplift it, leaving more latitude for a recovery in price by underperformers. This fits De Bondt and Thaler’s (1985) evidence that, over three years, a portfolio of previously underperforming stocks shows more price change, relative to index, than a portfolio of previously outperforming stocks.

This section has described the momentum effect, which appears, over time, to produce overpricing of winners and underpricing of losers but we have not explained why this effect occurs and this is a concern of the next section.

More On The Effect Of Information

Contrary to the efficient market hypothesis, there are many examples where there is initial underreaction to new information. One example is the failure to take account of changes in company satisfaction scores when these are announced. There is evidence that increases in satisfaction herald later increases in stock value (Anderson, Fornell and Mazvancheryl 2004, Aksoy et al. 2008, Luo, Homburg and Wieseke 2010). This evidence allows investors to benefit by buying/selling stocks in companies that have gained/lost on customer satisfaction ratings and investment on this basis has proved profitable (Fornell,
Mithas, Morgeson and Krishnan (2006; Fornell, Mithas and Morgeson 2009). Karam, Ryu and Yu (2022) found that basing investment on sentiment was advantageous and Yang (2021) found a strong relationship between investment sentiment and future stock prices. These cases indicate that, even when measured and reported, there is a delay in the response to information on market sentiment. Another example of underreaction, described by Edmans (2020), is that, after sensitive company announcements, there is an initial adjustment and then often a slow drift of price in the same direction; alert investors can gain an advantage from this drift. Here, Edmans offers two explanations. The first is that the diffusion of information is impeded by other information because the drift is slower when an announcement competes with a large number of other announcements or when it is made on a Friday and the distractions of the weekend affect response. Edmans’ second explanation attributes investor underreaction to confirmation bias. This is a person’s tendency to accept information consistent with their beliefs and resist information that is inconsistent (Wason 1960). This produces a bias in favor of the status quo and a reluctance to endorse evidence that is inconsistent with it. However, confirmation bias, though clearly observable, does not appear to confer any adaptive advantage and has not been well explained. We add a third explanation for the drift: that information diffuses slowly through social contacts and media comment so that there is a delay before these influences increase the purchase pressure on a stock.

In 1982, Tversky and Kahneman introduced the availability heuristic: information that is easily retrieved from memory (more available) is assigned greater probability and given more emphasis in judgments. Ease of retrieval rests on frequency of experience and other factors that make information more salient, such as relating to hopes and fears, being learned through experience, rather than from reports, and when it concerns events rather than states. It is likely that well justified information is more frequently experienced which provides an associative basis for the availability effect. Confirmation bias is probably based on the more frequent statement of well accepted ideas, which builds belief in these ideas through availability. One of the consequences of the availability mechanism is a greater emphasis on current information, which is more available, compared to past recollections and future predictions; this greater weight placed on current information supports status quo bias. Thus availability helps to explain both confirmation bias and status quo bias.

Is Tesla Overpriced?
At the end of November 2021, the stock price of Tesla was 22 times that which applied two years previously giving Tesla a value eight times that of Volkswagen and over three times that of Toyota. Tesla’s production of cars was approaching one million a year in 2021 but Volkswagen and Toyota were each producing 10 million. If Tesla continues to expand at 40 percent per year, it will reach the current output of Volkswagen or Toyota in seven years but competition from these and other automotive firms in the electric vehicle market is building up and this is likely to affect Tesla’s sales and margins. In these circumstances, the high valuation of Tesla seems unjustified.

The momentum effect may be partly based on availability. When there is a shock of positive information about a firm, this more available information will tend to support stock price increases, and these
increases then add to the current positive information. Media comment and word of mouth will then bring these changes to the attention of others, which will produce further upward pressure on price. This positive feedback may be why the momentum effect seems to overrun. A corresponding effect of negative information may lead to an overreaction against a stock, depressing its price. However, we should qualify what is meant by information here. Momentum effects seem to occur when there is some evidence relating to profit but uncertainty about the impact. For example, in the case of the Deepwater Horizon disaster, it was clear that crude oil was seeping into the Gulf but the eventual cost was quite uncertain. Similarly, the potential of Tesla is uncertain and it seems likely that momentum has led to an overpricing of this stock (see box). In this context, we should note that investors do not usually search for information systematically; Loibl and Hira (2009) found that 78 percent of US investors practised low to moderate information search.

We would expect well specified financial information to reduce momentum effects by making the fundamental value clear, so momentum effects should be stronger when such information is unavailable. Factors that persistently bias prices are not likely to produce momentum effects. For example, Aspara and Tikkanen (2008) showed that those who bought a company’s products were more likely to invest in that company and Barber, Heath, and Odean (2003) showed that the prestige of companies raised interest in investing in them; these propensities will produce a continuing pressure on price, rather than a momentum surge. Momentum effects are more likely to be started by novel information that has an unclear and potentially large impact on the profits of a firm. Examples could be that a large fine is levied on a firm, new mineral deposits are discovered by a mining company, or that there were signs of a takeover bid. Such information may be acquired from comment in newspapers, through Google searches, from websites such as Reddit, and through interpersonal contacts. Essentially, this sort of information increases the prospect of gain or loss but is not definitive. Rather, it focuses attention on a firm, raising speculation about its prospects and, as a result, increases the number of buyers/sellers. We can see this in the case of Tesla, where the advances in battery design and the prospect of near-autonomous vehicle guidance drew attention. Those who bought Tesla early have done very well so far (time of writing: November 2021) but it looks as though their gain is partly based on psychological processes. It seems likely that the most important information promoting momentum is a recent change in stock price. Support for this view comes from evidence on the cryptocurrency market where momentum effects are common (Borgards and Czudaj 2020). In this market investor sentiment is a guide to future price movement and it seems likely that this rests heavily on recent price movements because there is little else to indicate value (Gurdgiev and O’Loughlin 2020).

Uncertainty about stock value may be indicated by volatility in the stock price but other more direct measures of uncertainty could be useful predictors of momentum proneness. One direct measure is the number of Google searches. Preis, Moat and Stanley (2013) found that increases/decreases in the Dow Jones Industrial Average were preceded by a decrease/increase in search volume for certain financially related terms. However, Challet and Ayed (2013) argued that biases were present in this work and found no effect in a modified research design and Giorgio and Gutsche (2017) did not find that strategies based on search were helpful. One problem here is that people may search when they are considering either
investment or divestment and the reason for search may not be known. This may be behind the mixed results from other studies. Bijl et al. (2016) found that Google searches indicated marginally negative returns in contrast to Da, Engelberg and Gao (2011) and Kissan, Babajide and Wintoki (2011) who found positive returns in the two weeks following search, with reverse effects for longer periods.

Explaining Covid-19 Price Movements

We now return to the four ‘irrational’ stock price effects during the Covid-19 pandemic noted earlier and relate these to psychological explanations.

The delay before prices fell

One possible explanation here is a herd effect based on conformity. In uncertain situations, people pick up signals from others on what they should do and, when other people are doing nothing, that is what they copy. A second explanation is a failure of perception. Before widespread infection had developed, and a lockdown was necessary, investors might have found it difficult to grasp the likelihood of these changes. This is the negative side of the availability effect: what has not yet happened is harder to bring to mind and, consequently, has reduced impact. A further constraint on action may have been a reluctance to realize a loss, which, as reviewed earlier, has a number of explanations.

The overshoot when stock prices did fall

Once the fall had started, reality was thrust upon investors and the same mechanisms would impel the rapid decline and overshoot of stock price. The decline had become an event and was thus more available. The sell-off showed that others felt that prices were unsustainable so that any herd effect now favored selling. To check such a decline, the conventional view is that investors need evidence that stocks have lost more value than could be justified by an assessment of fundamentals, but such evidence may be difficult to source in a bear market and, even if available, may be crowded out by other (negative) information. The overshoot of the market seems to fit the pattern of the momentum effect. As stocks fall, the diet of stock price information is predominantly negative, which leads to more selling, a falling price, and, thus, more negative information. The availability of this information strengthens its influence and the dramatic quality of a stock market crash raises discussion leading to the diffusion of views through social networks and media. Although it is market lore that bear and bull markets overshoot, there seems a dearth of studies that quantify the overshoot. One would expect the extent of overshoot to be a function of the rapidity of the price change because corrective information would have less time to act under such circumstances. The rate of increase in price of the winners such as Zoom, Ocado, Asos and Amazon was much slower than the fall in price of the losers. Subsequently, these stocks lost value but at a much slower rate than the decline in value of stocks when the pandemic first hit.

The initial failure to recognize the advantage of online firms

When we consider the high level of understanding that we have achieved in many fields, it is tempting to credit human beings with great insight and to be perplexed by their failure to see the likelihood of a
lockdown and the consequential advantage to online firms. However, when we look carefully at the way in which innovative advances have occurred, these are usually achieved by piecemeal changes and often rest on serendipity or trial and error rather than insight (Ridley, 2020). Insight seems a fairly scarce phenomenon (East and Ang 2020). It appears that few investors anticipated a lockdown and the advantage this would give to firms such as Asos and Amazon.

**The slow rise of the winners**

We may like to think of ourselves as purposive forward-looking agents but the reality seems to be that we are driven more by past experience and currently available information than by a vision of the future. Status quo bias may restrain the rise of the winners and this slow rise is also explained by Helsen's (1964) adaptation-level theory. People develop price references, based on their experience, which are adaptation levels. When new experience is different from the adaptation level, the level will shift toward the new experience. This means that, in a market that is moving in one direction, the adaptation level operates as a drag on change. This does not explain why the fall of the losers was faster than the rise of the winners. Leverage differences may be part of the explanation here, but negativity bias is also a likely contributor.

**The Flow Of Information**

This analysis indicates that one key to predicting momentum effects is the flow of inexact information. Research on the diffusion of innovation through social networks has been conducted in a number of disciplines. There is general agreement that diffusion starts when external forces, such as advertising or news reports, act on individuals in the social network. This causes adoption/acceptance by early adopters who then influence others by word of mouth and example. In the case of new durables, widespread adoption tends to follow an S-shape distribution: adoption accelerates, reaches a maximum rate and then decelerates. This has been represented mathematically by Bass (1969) with parameters for the response to the external force, the response to other individuals in the social network, and for the final number of adopters. However, we do not know much about the way in which investment related information is exchanged between investors, and between media and investors. Google searches provide some indication of investor interest; Drake, Roulstone and Thornock (2012) found that there is increased search starting two weeks before earnings announcements and this search continues for a period after the announcement.

In the consumer field, much of the diffusion of new information occurs as word of mouth or as Internet comment. The great majority of positive comment on brands is made by current or past users (East, Romaniuk and Lomax 2011). In consequence, the volume of positive word of mouth about a brand is closely correlated with its market share in the category (Uncles, East and Lomax 2010). East et al. (2011) found that most negative word of mouth came from past owners. This means that new entrants to a market enjoy a honeymoon period during which the dearth of past owners reduces the level of negative comment. These patterns are likely to be reflected in comments on stocks; that is, we would expect most investor references to a stock to come from those who own, or have owned, that stock, that negative
comments would come more often from past owners, and that innovative offerings may, for a while, be less critically reviewed. However, the brands in a category often differ little; there is much more variability between categories. Firms are diverse and correspond more with categories than brands. Two categories with much the same sales volume can differ substantially in the amount of comment they attract. Similarly, firms with the same capitalization can have quite different breadths of ownership and, as a result, different levels of publicity and word of mouth. This suggests that one indicator of momentum potential is the volume of word of mouth/search/publicity in relation to capitalization. We expect more impact on stock price when this ratio is relatively large.

**Firm/Stock characteristics and the number of investors**

Publicity and word of mouth about a firm will relate to the number of its investors but the impact of any publicity on stock price is likely to be diluted by large capitalization; this focuses attention on factors that raise the ratio of the number of investors to capitalization. This ratio increases if the product attracts attention: cell phones are more interesting than bleach. Firms that sell products to individual consumers rather than to other firms and those that use more advertising will also widen the pool of people familiar with the firm (Fehle, Tsyplakov and Zdorovtsov 2005, Mathur and Mathur 1995). Demand for the firm’s stock may also be increased if it provides products, such as luxury cars or cruises, that are bought by those who tend to buy stocks. The size of a firm is often seen as a basis for stability but momentum effects are seen in both large and small companies and it is noticeable that the very large tech firms can show substantial fluctuation.

**Sources**

Word-of-mouth surveys (covering both positive and negative comment) are conducted by the Keller Fay Agency, now part of Engagement Labs; their method is described by Keller and Fay (2006). Customer satisfaction surveys are conducted in many countries using the American Consumer Satisfaction Index developed by Fornell et al. (1996). In the case of investments, debate on stocks may rest more heavily on media comment in newspapers, Google searches and specialist sites on the Internet. If this is the case, text mining should provide some indication of interest. Valle-Cruz (2021) has reported on the association between Twitter comment and stock performance. Google Trends may also be relevant but the evidence reviewed previously suggests that there is limited association with stock purchase, perhaps because a search does not indicate whether the interest relates to buying or selling.

**Diffusion of interest to new investors**

Studies of new product diffusion have dealt with products where price is relatively fixed and supply is flexible. In stock trading the supply is relatively fixed since most trades are covered by ownership so that price, rather than supply, varies. Changes in price alter the value of holdings and investors may, under these circumstances, increase or decrease their holdings. When holders sell, their stock may be purchased by other existing holders or by new investors. Take up by new investors indicates diffusion of interest in the stock which may indicate increasing momentum when it is accompanied by a rising price. If the price
is not rising, the new buyers may be late comers who have missed the boat. Thus, the changing ratio of new to existing purchasers in association with price could be a useful indicator of momentum potential but no research has been found on this matter. The ratio of new to existing stockholders, or the related measure of repeat purchase rates, could be established by a review of purchases by large stockbrokers or by stock exchange analysis. It should be noted that repeat purchase in the consumer field is highly predictable when markets are near-stable, as most are, and departures from the repeat purchase rate are used to detect rising or falling interest in a brand (Ehrenberg, Uncles and Goodhardt 2004). One problem affecting the recording of stock purchase is the large number of trades conducted by program traders. It is the change in the holdings of new and current investors that is of interest.

**What is to be predicted by AI?**

Those recommending stocks will often give a target price or will argue that the shares are currently undervalued by a given amount. This is useful for those following the Warren Buffet strategy of long-term investment. Those who want to take advantage of momentum effects need a rather different stock price prognosis where change in value is predicted with respect to the time elapsing from the present. What concerns the momentum investor is the stock’s rate of gain (or loss in short selling). For example, a stock might be predicted to gain substantially in value over the next three months and thus offer a short-term gain. On this basis it might be bought and then continuously reassessed until its prospects fall below those of an alternative investment. Following this thinking, an AI analysis should provide predictions of the likely rate of gain from the present time. Trades could be automated but, when human intervention is preferred, the analysis could provide recommendations to hold or switch investments. In addition, there will be considerations of portfolio management with some balancing of exposures across countries and types of firm; this can be handled by AI.

**Public interest**

This type of investment may be classed as speculation, which attracts an element of disapprobation. Investment based on momentum may misallocate capital by enlarging the size of bubbles and the depth of falls. Those who regulate markets should take steps to minimize such overshoots in price. To curtail speculative surges, credible predictions of profit impact are required. This may be impossible with disasters such as Deepwater Horizon but in other cases, such as Tesla, firms can project future returns using a range of scenarios. Firms may be reluctant to engage in such exercises, but it is a task that could be performed by auditors. Financial journalists do give predictions about share prices but these often lack detail and may foster rather than calm momentum effects.

**Conclusion**

We reviewed the psychological and social mechanisms that drive stock prices and asked what data are needed to enable AI to predict psychologically based price movements. Relevant mechanisms that may affect the behaviour of investors include the disposition to sell rising rather than falling stocks, disproportionate reactions to negative information, the stronger impact of more available information,
greater momentum effects in the face of uncertainty, more potential for the spread of information when stock ownership is large in relation to capitalization, and the take-up of stock by new investors. Thus, data that indicate the operation of these mechanisms may be of value. It is clear that financial data on the trajectory of price changes is important and that the characteristics of firms may also be indicative. In addition, effects may be stronger when the price movement is negative. Social data may add to the picture; evidence from word-of-mouth, satisfaction surveys and Internet search activity may assist. We identify two types of data that could help to predict momentum effects which are not currently cited. These are change in the proportion of new stockholders with rising price and indicators of interest/word of mouth/publicity in relation to capitalization. If AIs are trained on these kinds of data, they may learn to predict stock price movement that arise from investor psychology in addition to movement based on stock fundamentals.

References

12. Callaway E (2020) 'It will change everything': DeepMind's AI makes gigantic leap in solving protein structures, 'It will change everything': DeepMind's AI makes gigantic leap in solving protein structures...
44. International Journal of Forecasting, 27(4),1116–1127


61. Rosenbaum E (2017) AI assault on stock market: IBM’s Watson is getting into ETF business (cnbc.com)


Figures

**Figure 1**

DOW

---

GBP

---

© 2021 FactSet
Figure 2

FTSE 100

© 2021 FactSet

Figure 3

Carnival

© 2021 FactSet

Figure 4

Carnival
Figure 5

United Airlines

Figure 6

Amazon
Figure 7

Asos

Figure 8

Zoom
Figure 9

Ocado