

Mechanisms of Impact of Investor Behavioural Biases on the Performance of Quantitative Investment Models

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Abstract. This paper uses literature analysis and theoretical reasoning to examine how investor behavioural biases affect the performance of quantitative investment models. It is believed that overconfidence, herding behaviour and loss aversion, as well as the disposition effect that may result from loss aversion, do not directly affect returns but rather do so through other channels. Specifically, these behavioural biases first change trading behaviour and market conditions, and then modify the meaning of traditional variables such as price, trading volume, volatility and asset correlations, as well as the relationships among these variables and prediction results. That is, overconfidence leads to noisy trading and an underestimation of risk; herding behaviour magnifies market trends but also increases crowded trades and correlations, and the disposition effect can cause investors to delay the recognition of losses and thereby concentrate the realisation of losses over particular periods. Based on the above, this paper adds interaction terms between behavioural states and traditional market variables to the quantitative model to identify changes in market regimes and improve risk control. Based on the above theory, behavioural indicators can be employed as moderators to adjust the effects of traditional signals in various risk scenarios; however, they should not replace price, fundamental and risk data. As this is a theoretical rather than empirical study, the proposed mechanisms have not yet been validated using data from different financial markets.

Keywords: behavioral finance, quantitative investment, investor behavioral biases, market conditions, interaction terms

1. Introduction

In recent years, financial market data have become more easily available, and with the development of computer technology and statistics, so too has investment research. These developments have promoted the growth of quantitative investment. Most quantitative investment models build indices based on prices, trading volumes, company financial information and economic indicators. Using these data, quantitative models seek to identify relatively stable patterns in asset returns to predict returns, allocate portfolios, and control risk. Compared with investment methods based on individual experience, quantitative models have relatively clear rules, can be repeatedly tested through the same means, and it is convenient to compare the results in different market conditions. In addition to the amount of computing power and data, many other unstated assumptions must be met for a

quantitative model to work properly. According to the efficient market hypothesis, public information is rapidly reflected in asset prices [1]. Based on the above, many quantitative models also assume that market participants process information reasonably rationally and that the relationships shown in historical data will have some relevance in the future. Therefore, to ensure the stability of the historical relationship, out-of-sample evaluation is required to assess the stability of historical relationships. Factors, volatility estimates and asset correlations that have been effective in the past may continue to work only if there has been little change in the market structure. Changes in investor behaviour, market institutions or the trading environment may have altered the relationships seen in the past data.

Real markets do not fully meet the assumptions of investor rationality and stable market relations. Investors are afraid of losses, but several consecutive gains may make them too confident in their own judgment. Kahneman and Tversky put forward the theory of prospect, and people are generally more averse to losses than they are to gains [2]. Other typical behaviours in the financial market are excessive confidence, imitation of the trading behaviour of other investors, failure to limit losses in time, pursuit of higher prices, and panic selling. The behaviour bias of one investor will not significantly alter the market. However, when many investors make trades in the same direction due to similar emotions, prices, trading volume and risk levels will all be affected. For example, when the market is performing well, more people will buy in hopes of making a profit. The increase in price will attract more investors, and so on. Therefore, not all changes in price are due to an increase in corporate value; they can also be caused by changes in sentiment and concentrated capital flows.

Quantitative models usually use the actual indicators directly, such as price, trading volume and volatility, but fail to explain the reasons for the changes in these indicators. A sudden rise in trading volume may be due to an important announcement by the company or simply an increase in trading activity by investors. A prolonged rise in prices may be due to higher income, or it may also be caused by changes in the market and reduced supply. If the model thinks the above cases are the same problem, its predictions will likely be off. Investor behavioural biases can therefore affect quantitative models indirectly. First, these biases change buying and selling behaviour in the market; they then affect prices, trading volume, volatility, and correlations; finally, they alter how the model interprets these data. Therefore, this helps explain why the same factor performs very differently across different market stages. It can also be determined whether the model failure is due to a problem with parameters or to a change in the market environment.

Behavioural finance and quantitative investment research can be combined to provide an explanation for the micro-level behavioural reasons for the failure of quantitative models. Behavioral finance is mainly about why investors are not rational, and quantitative investment research generally focuses on factors, algorithms and prediction results. These two strands of research have often been examined separately, although they are closely related. The market data used by quantitative models are not entirely objective; they also contains investors' opinions, emotions and so on. There are also some practical problems. Many investment institutions set positions according to the historical volatility, asset correlation and maximum drawdown. However, when the market is in a different state, the representativeness of the historical data may drop sharply. A long period of low volatility will probably cause the model to underestimate the actual risk and increase the correlation among assets significantly in a market downturn. A model can also find abnormal turnover, crowded trading and changes in investor sentiment to know about changes in the market sooner. Behavioural variables cannot replace the use of price, fundamental and risk data, but they can help prevent model users from blindly extrapolating the relationships observed in the past.

This paper employs literature analysis and theoretical reasoning rather than comparing the returns of different quantitative strategies. It first reviews research on quantitative investment models and investor behavioural biases. It then introduces the theoretical foundations of quantitative investment and behavioural finance and analyzes how overconfidence, herding, and loss aversion may affect model performance. Finally, the paper discusses the incorporation of behavioural variables into traditional quantitative models, summarizes the main findings and limitations, and proposes directions for future research.

2. Literature review

2.1. Research on quantitative models

A quantitative model will convert the large amount of financial data into calculable indices. Quantitative models use prices, trading volumes, financial indicators, and macroeconomic data to construct factors for predicting future returns or estimating risk. Therefore, the performance of a quantitative model should not be evaluated solely on the basis of its realised returns. Even if a model has achieved a good return over a certain period, it cannot be concluded that it will remain so in the long run. Evaluation should also consider prediction stability, the rate at which factor effects decay, the reliability of risk estimates, and the adaptability of the model to changing market conditions.

With the increase in the amount of data available, quantitative research can be based on more types of data. News, search records, social media and images are also being used to assess the market's mood. Obaid and Pukthuanthong used machine learning to identify the emotions in news pictures and found that this kind of data was not covered by the traditional factors [3]. Therefore, it can be seen that market sentiment can be inferred from changes in price, and news content itself can also be used as a model input. Mavruk employed machine learning to study herding in the portfolios of individual investors [4]. According to the above study, because investor behaviour cannot be observed directly, it can be inferred from changes in stock holdings, trading direction, and other observable trading activities. The above studies have increased the amount of data for quantitative models, but adding more variables does not guarantee that the model will be more reliable. Models are still trained on historical data, while market conditions may change substantially over time. A market crisis, asset bubbles and sudden changes in sentiment can all cause a rapid decline in the prices of assets that were previously stable.

For example, a factor may be good for a long time in a normal market, but after many market participants have begun to use the same strategy, its performance will change. A model may not perform well because of calculation errors; it is also possible that the market has changed since the model was built. Gong and others and Jiang and Jin have explored the link between investor sentiment and market fluctuations [5, 6]. Based on the above research, only the traditional market variables are insufficient to explain the changes in risk. At the same time, in times of crisis, the fluctuations in prices will be relatively large.

Some studies have already added the sentiment index to the quantitative model. However, many of them only examine whether prediction accuracy improves with the addition of these variables and do not investigate the underlying reasons in detail. For example, an increase in trading volume may be due to the release of new information in the market, or it may just be random fluctuations. These two situations are not equivalent for a model. Accordingly, this paper examines how changes in investor behaviour affect the interpretation of market data and, in turn, the performance of quantitative models.

2.2. Research on investor behavioural biases

The first idea of behavioural finance is that people's behaviour in investment decisions is not always rational. Limited information, market volatility, time pressure and changes in emotions all affect people's judgment. Overconfidence is a typical behaviour bias. Investors may be overconfident in their analysis, assume that any small gain resulted from a good decision, and thus increase the frequency of trading. Barber and Odean did not find that frequent trading increased the investment return; rather, it increased transaction costs [7]. The above finding indicates that active trading is not necessarily associated with more information in the market. An increase in trading volume may be due to the investors' overconfidence in their own judgments and not to the release of more valuable information.

Herding often arises when investors have insufficient information about market conditions. When investors are unsure about the trend of the market, they may look at what other people are buying and selling for a signal. Bikhchandani and Sharma have provided an organised discussion on herding in financial markets [8]. It is especially serious in times of economic downturn. Espinosa-Méndez and Arias observed an increase in herd behaviour of the Australian stock market during the COVID-19 pandemic [9]. Ah Mand and others also found that the herding behaviour changes with changes in the market [10]. Herding will raise the price temporarily, but it may also cause many investors to hold the same assets. With increasing trading concentration, a reversal in market direction may cause many investors to sell simultaneously, leading to a sharp decline in prices.

Loss aversion and the disposition effect are not the same thing. Loss aversion is a type of psychological bias; people are more averse to losses than they are to gains. The other is the disposition effect; that is, people tend to sell profitable stocks too soon and hold onto losing stocks for too long. Brown and others carried out a meta-analysis and found that loss aversion is widespread but of different strengths [11]. Fan and Neupane believe that the investment period and investment experience affect the disposition effect [12]. The two ideas may be connected, but the disposition effect should not be taken as the definition of loss aversion or an inevitable result of it.

Investor sentiment indicates the general mood of the market, whether it is optimistic or pessimistic. Baker and Wurgler find that investor sentiment has a stronger effect on stocks that are difficult to value, have limited information and are subject to stricter limits on arbitrage [13]. Wang et al. show that stock returns are associated with changes in investor sentiment, although the strength of this relationship varies across markets [14]. Cevik and others have also found that the links among investor sentiment, stock returns and volatility are more pronounced in times of high uncertainty [15]. Therefore, the effects of investor sentiment may vary across market conditions and levels of uncertainty. In a stable market, the impact of sentiment will be relatively small; in a period of market turmoil, it will change the price of stocks suddenly.

In short, all the above studies have found that behavioural biases affect trading volume, stock returns and market volatility. However, the effect on the quantitative model is not mentioned here. Most of the research on behavioural finance has focused on investors and markets, and many quantitative studies have used prices, trading volumes and volatilities as the input variables. The two parts will be linked in this paper to show that behavioural changes first appear in market data and then affect the predictions and risk assessments of a model.

3. Theoretical basis: quantitative investment models and behavioural finance

3.1. Theoretical basis of quantitative investment models

A quantitative model can be regarded as a set of rules for making investment decisions based on market information. After the data enters the model, the following steps will be carried out: factor construction, prediction, asset allocation and risk control. Although the above process can be performed automatically, it is not completely independent of people. Researchers still need to decide which variables to use, how long to set the historical window, how to set parameters, and when to determine that the model is no longer effective. Although a computer can execute the trades, people are still responsible for the model's initial design and modifications.

The general form of a quantitative model can be written as follows:

$$Y_t = f(X_{1,t}, X_{2,t}, \dots, X_{n,t}) + \varepsilon_t \quad (1)$$

Here, Y_t is the target variable that the model seeks to predict at time t , such as a future return, volatility, or risk level; $X_{1,t}$ through $X_{n,t}$ are market, fundamental, or macroeconomic variables available at time t ; and ε_t is the error term that cannot be explained by the existing variables and model structure.

A model estimates the relationship between X and Y from historical data and then applies that relationship to future predictions. The problem is that the relationship may not remain stable over time. If market conditions change, the same variable may no longer carry its original meaning, and prediction errors may increase. Trading volume provides a straightforward example. Under normal conditions, higher trading volume may indicate that the market is absorbing new information. When overconfidence or return-chasing sentiment is strong, however, higher volume may simply reflect more frequent trading. In both cases, the observable data show an increase in volume, but the underlying causes are entirely different. If the model cannot distinguish between them, it may mistake noise for a valid signal.

3.2. Efficient market hypothesis and the assumption of rationality

According to the efficient-market hypothesis, new public information is quickly reflected in the prices of assets through trading. If asset prices deviate substantially from their fundamental values, arbitrageurs may trade against the mispricing and push prices back toward equilibrium levels. Quantitative models do not need a fully efficient market, but they generally assume that changes in prices contain a considerable amount of useful information. Many conventional quantitative strategies are based on this principle. For example, historical volatility can be used to determine position size, while past correlations between assets can be used to diversify a portfolio. These approaches are not inherently problematic, but they rely on an implicit assumption that market structure does not change substantially over short periods.

Arbitrage in actual markets also has many restrictions. Arbitrageurs will not enter the market on time because of high transaction costs, capital constraints, the lack of short-selling rights and low risk-bearing capacity. Therefore, although the prices are out of line, they will not be adjusted immediately. When many investors are swayed by the same emotions at the same time, mispricing may continue for a long time. Therefore, the price and trading amount also show whether there is imitation or panic among investors, as well as changes in sentiment.

3.3. Behavioural finance theory

Behavioural Finance does not assume that investors are fully rational. Therefore, investment decisions are subject to various biases and are affected by emotions and society. Quantitative models do not themselves exhibit psychological biases; however, the market data they process are generated by investors whose trading decisions may be influenced by such biases. If investors change their behaviour, prices and trading volumes will change; thus, the quantitative model will be affected as well.

Investor behavioural biases first affect buying and selling decisions, which subsequently alter market data and influence model predictions, factor performance, and risk estimates. Market data are not the end results; they are the links connecting investor behaviour and quantitative models. This paper therefore focuses on three questions: First, does behavioural change reduce predictive accuracy? Second, does it weaken the effectiveness of factors that performed well historically? Third, does it cause risk models to underestimate volatility, asset correlations, and extreme losses? Together, these three dimensions provide a basis for evaluating the stability of quantitative models under changing market conditions.

4. Mechanisms of impact for investor behavioural biases on the effectiveness of quantitative models

4.1. How overconfidence affects quantitative models

Overconfidence is not just high self-confidence; rather, it is an underestimation of the likelihood of making mistakes. After several consecutive gains, some investors may attribute the results entirely to their own ability and overlook the role of market conditions or luck. Then they may trade more often or increase their positions without having all the information. As a result, trading volume may increase, although these additional trades may contain little new information. Some trades will only be reflections of short-term price changes.

Therefore, a model that relies only on trading volume and short-term price fluctuations may perform poorly. For example, if the whole market is in a good mood and many people are buying stocks, the price of those stocks may rise quickly. A trend model may determine that the rise is the start of a prolonged trend and issue a buy signal. If the company's fundamentals have not changed significantly, the price will fall due to reduced sentiment. The problem is not necessarily that the trend signal has little value, but that the model cannot distinguish whether the trend reflects new information or excessive trading.

Overconfidence can lead investors to underestimate market risk. The longer the rise of a market, the more likely investors are to believe that market risk has fallen. Some people may believe that past profits show that they will continue to make money in the future, thus gradually taking on more risks. If market volatility remains low for a prolonged period, a model calibrated to recent data may continue to underestimate the true level of risk. After the market changes, the actual fall will be much larger than the one predicted by the calm-period data.

Overconfidence therefore affects quantitative models through two main channels. First, greater market noise may reduce the informational content of trading volume and short-term price signals. Second, there will be an underestimation of risk in a rising market. High trading volume and rapid price fluctuations do not necessarily mean that the market has more information. In some cases, it shows that the investor has been keeping the same position repeatedly.

4.2. How herding affects the efficiency of quantitative measurement

Herd behaviour is when investors are no longer guided by their own information but are instead influenced by the trading behaviour of other investors. When a type of asset starts to rise, later investors will also buy because they have seen others do so. Their purchases are raising prices and thus increasing the extent of the price rise. Under such conditions, momentum or trend-following strategies may temporarily generate higher returns. However, the above results do not indicate that there has been an actual change in asset value. The rise in price is due to a concentration of capital inflow.

As more investors follow the same trading direction, trading becomes increasingly concentrated. If some investors start taking profits, others will quickly follow suit and sell. The previous self-reinforcing trend can be quickly reversed, and the profits obtained by the model in the early stage may be lost in a short time.

Herding will also decrease the advantage of diversification. In normal times, different assets will react differently to news about their respective companies and will thus have relatively low-price correlations. In a market panic, many investors are selling stocks, commodities and other risky assets at the same time. As a result, even though the portfolio is constructed based on historical correlations and includes many different assets, it may still be subject to the same market sentiment. The risk that was previously spread out will likely be concentrated at a bad time.

Therefore, herding may temporarily strengthen the performance of trend-following strategies, but excessive crowding can make such performance unstable. Therefore, the strategy's performance will be affected by changes in the market. At the start of the trend, a model will probably be the subject of concentrated trading. If the market becomes too crowded, there will be price drops, reduced liquidity and an increase in asset correlations. The problem of a quantitative model is not that there is a trend, but rather whether trading according to that trend has already become overly concentrated.

4.3. How loss aversion and the disposition effect affect risk models

Most of the old risk models only consider volatility, asset correlation and past losses. However, the response of investors to losses is not fully reflected in these figures. First, one needs to distinguish between loss aversion and the disposition effect. Loss aversion refers to the tendency for losses to have a greater psychological impact than equivalent gains, whereas the disposition effect describes the tendency to sell profitable assets too early and hold losing assets for too long. Loss aversion and reference dependence may be reasons for the disposition effect, but they are not the same.

A disposition effect is that investors continue to hold on to assets that have lost value in the hope that prices will rise to the original purchase price, and thus fail to re-evaluate the value of these assets based on new information. As a result, observed short-term volatility may remain low even though underlying downside risk continues to accumulate. As investors do not sell immediately, the bad news will not be reflected in a sudden drop in prices, and short-term fluctuations will remain relatively small. However, it does not mean that the risk has gone away; the selling pressure may have only been postponed.

If prices continue to fall, there will be reduced funds, margin calls and panic selling by investors. If prices continue to decline, delayed selling may eventually turn into concentrated liquidation, accompanied by higher volatility and stronger asset correlations. Models that use only data from stable periods will probably underestimate the size of the loss in this case. The model will give a

small weight to an abrupt decline in price, but the extended sale will increase risk for the time being due to the disposition effect.

The disposition effect will change the portfolio. Investors will continue to hold on to the underperforming assets and sell the profitable ones. Over time, the portfolio will be out of line with the original allocation and may have increased risk concentration. The real problem with a quantitative risk model is not that investors are afraid of losses; rather, it is that their behaviour changes the speed at which risk accumulates and how it is finally released.

4.4. A behavioural adjustment mechanism for quantitative investment models

This paper does not treat behavioural variables as substitutes for traditional return signals. Instead, it treats them as moderators of the relationships between traditional market variables and model outcomes. The main hypothesis is that when investor sentiment, abnormal turnover, the degree of herding or crowded trading change, then the relationships among the traditional variables—price, trading volume, volatility and fundamentals—and next-period returns or risk will also change. Therefore, the improvement of the model should focus on testing the interaction between behavioural states and traditional variables, and not add direct effects of behavioural variables.

The proposed specification is a conceptual analytical framework rather than an empirically estimated model. The revised relationship can be written as follows:

$$Y_{t+1} = \alpha + \beta M_t + \gamma(M_t \times B_t) + \varepsilon_{t+1} \quad (2)$$

Here, Y_{t+1} represents the next-period return, volatility, or risk level; M_t represents traditional market variables such as price, trading volume, volatility, and fundamentals; B_t represents behavioral states such as investor sentiment, abnormal turnover, the degree of herding, and crowded trading; and $M_t \times B_t$ is the interaction term. β represents the relationship between traditional variables and the prediction outcome in the baseline state, while γ indicates the extent to which a change in behavioral state alters that relationship. Therefore, when B_t changes, the marginal effect of M_t on Y_{t+1} changes from β to $\beta + \gamma B_t$. The formula does not include a separate direct effect for B_t because the paper's central argument is that behavioral states mainly change the meaning and effectiveness of traditional signals rather than independently predicting returns.

Sentiment indicators can help identify the forces driving price movements. News texts, search interest, social media content and capital flows can all show whether the market as a whole is relatively optimistic or pessimistic. For example, if search interest, turnover, and news sentiment are all high while prices are also rising, it is necessary to determine whether the price increase is driven by excessive sentiment. At this time, one can leverage the interaction between the behaviour state and the trend signal to reduce the weight given to the traditional trend signal by the model and avoid using sentiment directly as an index for future returns.

Interaction terms are added to account for market regimes and control for risk. When the market is relatively stable, the model can continue to be based on price and fundamental factors. When behavioural indicators signal unusually strong sentiment, abnormal turnover, rising asset correlations, or crowded trading, the model may reduce the weight assigned to short-term trend signals, lower position sizes, limit total risk exposure, or implement additional stress tests. Although this adjustment mechanism cannot accurately predict market peaks, it may help reduce excessive risk-taking during periods of unusually intense trading activity. Appropriate thresholds can be

introduced to adjust model parameters gradually while limiting unnecessary model complexity and the risk of overfitting.

However, this approach also has important limitations. Sentiment and herding cannot be directly observed; instead, they can only be indirectly inferred from news, search volume, trading volume and capital flows. These indices will have considerable noise. At the same time, sentiment affects prices, and changes in prices also affect sentiment; thus, there is endogeneity. Therefore, to determine whether the interaction terms can improve the performance of the model, out-of-sample predictions, robustness tests and data from different markets need to be used; they cannot be based solely on theory.

5. Conclusion

The central argument of this study is that even when the rules of a quantitative model remain unchanged, changes in investor behaviour can alter the market data on which the model relies. This mechanism does not imply that quantitative models themselves exhibit behavioural biases; rather, the data used to train and operate these models are generated by investors whose decisions may be influenced by behavioural factors. First, investors' judgments and emotions change the trading behaviour; then, they affect prices, trading volume, volatility and asset correlations, and finally change the signals obtained by the model. Too much self-confidence will lead to speculation and a reduced sense of risk in good times. Herding may amplify market trends in the short run, but it will also lead to crowded trades, price fluctuations and high correlations. Loss aversion is a psychological preference; when it is combined with reference dependence, it can lead to a disposition effect, and delayed selling may cause risk to accumulate first and then be realised in a concentrated manner.

These mechanisms share one feature: behavioral states change the relationship between traditional variables and prediction outcomes. A factor that was effective in the past will not necessarily remain effective after the market changes state. Similarly, low volatility and correlations during calm periods may not accurately reflect risk during extreme periods. Based on this view, the paper uses the interaction term $M_t \times B_t$ to represent the moderating effect of behavioral states on the effectiveness of traditional signals, rather than treating behavioral variables themselves as independent predictors of returns. This formulation is consistent with the paper's mechanism in which behavior first changes the meaning of data and then influences model judgments.

In practice, the following indicators can be added to the price, fundamental and risk data: sentiment, abnormal turnover, the degree of herding and crowded trading. These indicators can provide information about changes in market conditions and allow the model to adjust its risk controls accordingly. Behavioral indicators cannot replace the old data, and adding too many of them is not always beneficial. Only when these indicators have clear economic interpretations, pass out-of-sample tests, and exhibit reasonably stable cross-market interaction effects can they be regarded as reliable model inputs.

The main deficiency of this paper is that it does not apply the proposed mechanisms to real market data. It has listed some potential ways of influence but has not determined how large the effect of each behavioural bias is, nor has it been proven that adding interaction terms will increase returns or reduce risk. Another is that it is difficult to measure the behaviour state accurately. News sentiment, search interest and abnormal turnover are all indirect indicators and contain a lot of noise.

Investor structures and trading systems are also different in different markets, so the same indicator may have different meanings in stock, futures and cryptocurrency markets. For example, the increase in turnover may be caused by higher trading in the stock market; at the same time, in an

overleveraged derivatives market, it can be due to forced liquidations and short-term fluctuations in liquidity. At the same time, there are also overconfidence, return-seeking, herding behaviour and panic selling. This paper will introduce them separately for clarity, but in actual operation, they are more complicated.

In the future, behaviour-state indices will be constructed from news texts, social media, search data and investor trading records. Future research can then compare prediction accuracy, maximum drawdown, and risk-estimation errors before and after behavioural interaction terms are introduced. Only out-of-sample tests, rolling-window tests and multi-market comparisons can determine whether the behaviour adjustment has actually improved the model's performance or only increased the complexity of the model.

Artificial intelligence and machine learning can process unstructured data. Natural language processing can detect positive and negative words in the news, and machine learning can also find abnormal trading and crowded portfolios. The more advanced the technology, the more serious the problem of overfitting and the need for economic interpretability. More research can build behaviour-state-dependent models to adjust the weight of traditional signals and risk control based on sentiment, liquidity and trading activity. However, the robustness of these approaches should be evaluated over longer sample periods and across multiple financial markets.

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