# Measuring investor sentiment and behaviour to gauge financial risk

Received (in revised form): 12th July, 2008

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**Abstract** Whether financial markets are governed by rational forces or emotional responses has long been debated. The spectacular rise of commodity futures prices and the current plunge in value stocks have intensified the debate, highlighting that implied volatility is not an accurate measure of market risk. Asset managers traditionally assume irrational investor behaviour when creating and administering portfolios but this is hindered by a lack of diagnostic tools. In particular, they are unable to adapt to emotional and moderate cognitive biases at high wealth levels to modify investor behaviour at lower wealth levels. Henceforth, practitioners should rely on specific quantitative guidelines when modifying asset allocations to account for biased behaviour. As a result, specific quantitative guidelines must be followed when modifying asset allocations to account for biased behaviour. This paper proposes a framework for better understanding how behavioural finance can be associated with a classical approach in many areas of investing, including valuation. The paper will discuss key behavioural phenomena, notably market sentiment and noise trading, integrated as parameters in a new quantitative risk–return calculation. This comprehensive model will suggest acceptable discretionary distances from the mean–variance output for determining the best practical allocation. Finally, the paper compares the returns of so-called 'behavioural mean–variance portfolios' with those of traditional mean–variance-efficient portfolios.

***Keywords:*** *investor sentiment, risk premiums, behavioural mean–variance portfolio*

Most financial economists advocate the 'efficient markets hypothesis' (EMH),[1] in which prices are determined by the competitive trading of many self-interested investors and any informational advantages are eliminated. In such a transparent market, prices 'fully reflect all available information' and are therefore predictable. However, the large number of past crises immediately followed by flourishing periods have emphasised the presence of instability which belies the hypothesis of market efficiency. As an example of the impossibility of predicting movements with certainty and to give credence to the critics of market rationality, it took less than two years for the NASDAQ Composite Index to fall from its historical high of 5048.62 (10th March, 2000) to 1646.34 (17th October, 2001). Here, one might argue either that the run-up to the high point was characterised by unbridled greed and optimism in the technology sector, or that such a precipitous drop in value of such a significant portion of the US economy was due to irrational fears and pessimism. More generally, investors are often irrational, exhibiting predictable and financially ruinous biases such as overconfidence, overreaction, loss-aversion herding, psychological accounting, miscalibration of probabilities and regret.

Interestingly, recent research into financial economics and the cognitive sciences suggests an important link between rationality in decision making and emotion,[2] implying that the two notions are not antithetical. Statman was among the first to consider these human flaws as consistent, predictable patterns which are exploited for profit, writing that 'investors try to avoid the pain of regret by avoiding the realisation of losses, employing investment advisors as scapegoats, and avoiding stocks of companies with low reputations'.[3]

Psychologists have been progressively entering this field of financial research in an attempt to understand how emotions and cognitive errors influence investors' risk sentiment. Even if some academics have successfully explained market inefficiencies such as market anomalies, their empirical models have failed to describe how they can directly affect the decision-making process or be used in investment strategies. The out-performance of value investing usually results from investors' irrational overconfidence in exciting growth companies and from the fact that investors take pleasure and pride in owning growth stocks.

Thus, behavioural finance has evolved by studying the importance of emotion in the decision-making process of traders. During live trading sessions, Lo and Repin measured some physiological characteristics (eg skin conductance, blood volume, pulse, etc) while simultaneously capturing real-time prices from market events.[4] An investor's background and past experience can also play a significant role in their decisions. Women may be more risk averse than men, and passive investors have typically become wealthy without much risk, while active investors have typically become wealthy by earning it themselves.

Even if behavioural finance has become a subject of significant interest, a legitimate question arises: What exactly is behavioural finance? Its three main consistent objectives are the following:

- to integrate classical economics and finance with psychology and decision-making sciences;
- to attempt to explain what causes some of the anomalies (eg a bubble in commodity prices) that have been observed and reported in the finance literature;
- to study how investors systematically

make errors in judgment, or 'mental mistakes'.

By considering that investors may not always act in a wealth-maximising manner and that investors may have biased expectations, behavioural finance can be used to explain some of the EMH anomalies. Common axioms are that, in the short term, markets are inefficient and the potential exists for misevaluation; the mispricing can widen, and in some cases is likely to widen before it narrows. Market values are eventually assumed to revert to intrinsic values, although the long run might be very long. A new paradigm that reconciles the EMH with behavioural biases yields some surprisingly concrete insights when applied to practical settings such as asset allocation, risk management and investment consulting.

This paper takes a top-down approach to behavioural finance and the stock market, in which it attempts to measure investor sentiment. The first section discusses the adaptive markets hypothesis (AMH) framework to understand how behavioural finance must be embroiled in a neoclassical approach to risk appetite. Lo has previously underlined the qualitative and descriptive aspect of this new framework but without clear guidelines to take into account investors, general market sentiment and noise trading, in a consistent and intellectually satisfying manner.[5]

The remainder of this paper is organised under the assumption that waves of sentiment have clearly discernible, important and regular effects on individual firms and on the stock market as a whole. The equity risk premium is considered as not being constant through time, as all investment products tend to experience cycles of superior and inferior performance. Thus, market efficiency is not an all-or-none condition but a characteristic that varies continuously over time and across markets. Additionally, individual and institutional risk preferences are not likely to be stable over time. Furthermore, the paper will point out the importance of taking investor sentiment and noise trading into account in a tactical risk-adjusted asset allocation. The final section outlines several applications for the practice of investment consultancy prior to setting a new and broader risk perspective for the fund management industry.

The efficient markets hypothesis in its semi-strong form asserts that the current market price incorporates all available information about the security in question. In 1977, the Magellan Fund was small and obscure, worth a limited \$18m in assets. Thirteen years later, in 1990, this fund managed by Fidelity Investments was worth \$14bn. Peter Lynch is best known for his work with the Magellan Fund. He never had one specific investment style, but rather changed his strategies with changes in the market. He firmly believed that no one could predict fluctuations in the economy or interest rates and therefore suggested that people take the time to identify great companies in which to invest instead of taking long shots. Now, not everyone can do that; in aggregate, what is earned is the market return, less fees. The market is definitely efficient at a group level. But how can one explain persistently clever subgroups?

The AMH says that all market inefficiencies exist in a tension with the efficient markets, and that players beat the markets by looking for the inefficiencies, and profiting from them until they disappear. Rather than taking the neoclassical approach of attempting to maximise expected utility and assuming rational expectations, the AMH is a model in which 'the dynamics of evolution, mutation, reproduction, and natural selection determine the efficiency of markets and the waxing and waning of financial institutions, investment products, and ultimately, institutional and individual fortunes'.[5] This perspective implies that behaviour is not necessarily intrinsic and exogenous but evolves by natural selection depending on the particular environment through which selection occurs. There are speculative opportunities in the market,[6] but they appear and disappear over time, so innovation is the key to survival. Unsuccessful investors, the ones who continue to make maladaptive decisions, are eventually eliminated from the population. Using only qualitative analysis, Lo found that this model can explain certain counterexamples to economic rationality, such as loss aversion, overconfidence, overreaction, mental accounting and other behavioural biases.[5] Another advantage of AMH is that it can deal with bounded rationality and potential for opportunism. Although this model is currently only in a qualitative state, it does provide a new framework on how to think about financial markets.

The Santa Fe Institute Artificial Stock Market was developed by Brian Arthur, John Holland, Blake LeBaron, Richard Palmer and Paul Taylor in 1994. This model is an agent-based game model in which traders continually develop strategies to predict future prices in financial markets. The model allows one to observe some important elements of decision making in the financial market without having to assume perfect rationality. A fixed number of players N are each endowed with initial wealth W0. The game is played through multiple stages — time is measured at discrete intervals. At the beginning of each period, the players rely on their prediction strategy to determine what they want in their portfolio. They also have the option to change their prediction strategy to a more profitable one based on recent performance between investing in risk-free assets equivalent to treasury bills (which are supplied without limit) and risky stocks. The rate of return is a constant interest rate r, the opportunity cost a player faces for choosing a risky stock is r. There are N shares of the risky stock that pay an uncertain dividend d at the end of the period. All traders have an identical constant absolute risk-aversion utility of wealth function:

$$U(W_{i,t+1}) = e^{-\lambda W_{i,t+1}}$$

At each round, the players choose between the risk-free asset and risky stock independently, but the payoffs depend on the decisions of all of the players. Players have the option to revise their method of forecasting the stock's future price, so let the forecast revision rate refer to the rate at which players revise their stock-picking rules. They will choose to increase their revision rates because it is a strictly dominating strategy, even though everyone is better off if they can agree to slow down the revision rate of their market-forecasting rules. Although cooperation can emerge among self-interested players in iterated two-person prisoner's dilemmas, achieving this has been shown to be almost impossible in an N-person game.

In any case, the market's behaviour is consistent with the EMH if traders revise their forecasts infrequently, but is unsustainable due to the enforcement problems of dealing with a large number of market participants. At the equilibrium where all market players revise their rules frequently, trading systems become more sophisticated. In short, if the population consists of mostly speculative traders, the market will be volatile and inefficient. Agents are assumed to be subject to a variety of cognitive biases which are then shown to explain phenomena for which the standard model cannot easily account. Unfortunately, behavioural finance consists of a proliferation of essentially *ad hoc* models designed to explain a few asset pricing 'anomalies' and that there is no satisfactory underlying theoretical framework to compare with that of the standard model.

In the AMH proposed by Lo, forces that drive prices to their efficient levels are weaker and operate over longer time horizons.[5] Processes of learning and competition and evolutionary selection pressures govern these forces. Individual agents are no longer the 'hyper-rational' beings of the standard paradigm, but rather bound rational 'satisfiers'.

An initial application involves asset allocation decisions: the selection of portfolio weights for broad asset classes. If a relation between risk and reward exists, it is unlikely to be stable over time as it is determined by the relative sizes and preferences of various populations in the market ecology as well as institutional aspects such as the regulatory environment and tax laws. As these factors shift over time, any risk–reward relation is likely to be affected.

A corollary is that the equity risk premium is time-varying and path-dependent in the context of a rational-expectations equilibrium model as risk preferences change over time. A second implication is that arbitrage opportunities do exist from time to time. Without such opportunities, there would be no incentive to gather information and the price-discovery aspect of financial markets would collapse. A third implication is that investment strategies would also wax and wane, performing well in certain environments and performing poorly in other ones. In the classical EMH in which arbitrage opportunities are competed away, eventually eliminating their profitability, the AMH implies that they may decline for a time and then return to profitability when environmental conditions become more conducive to such trades. Cycles are not ruled out by the EMH in theory, but in practice none of its existing empirical implementations have incorporated these dynamics.

A final implication is that characteristics such as value and growth may behave like risk factors from time to time; that is, portfolios may yield higher expected returns during periods when those attributes are in favour. For example, during the US technology bubble of the late 1990s, growth stocks garnered higher expected returns than value stocks, only to reverse after the bubble burst.

While such non-'stationarities' create difficulties for the EMH, the AMH places no restrictions on what can or cannot be a risk factor whether or not a particular characteristic is priced. Because a significant proportion of investors prefer growth stocks over others, a growth-factor risk premium arises. As the number of growth-oriented investors dwindles, the growth premium declines and other characteristics may emerge in its place.

The natural question that follows is this: How does one determine which characteristics are priced and which are not? Although the AMH does not yet offer quantitative methods, some qualitative guidelines are available. The main determinants revolve around the preferences of market participants and how they interact with the natural resources of the market ecology. This suggests a specific research agenda for the risk management community to identify and value priced factors that coincide with the study of any complex natural ecosystem.

If one is to develop a basic but complete description of the market environment in which these investors are interacting (including natural resources, current environmental conditions and institutional contexts such as market microstructure, legal and regulatory restrictions and tax effects), one must provide summary measures of the cross-section of current investors' preferences and the population sizes of investors (with each type of preference). One must also specify the dimensions along which competition, innovation and natural selection operate. Armed with this data, it should be possible to tell which characteristics might become risk factors and under what kinds of market conditions. Even if gathering them is unprecedented and is by no means a trivial undertaking, this may very well be the price of progress within the AMH framework. The bottom line is that active asset allocation policies may be appropriate for certain investors and under certain market conditions. If changes in the investor population, investors' preferences and environmental conditions can be measured in a meaningful way, then it is indeed possible to construct actively managed portfolios that are better able to meet an investor's financial objectives. Whether or not the cost–benefit analysis supports active management is a different question, and depends as much on business conditions in the investment management industry — fee structures, total size of assets to be managed, and the amount of competition for assets and managerial talent — as it does on the magnitude and nature of the portfolio manager's skills. Moreover, measuring the kind of changes described here is no mean feat, especially given the lack of relevant data such as investor preferences, demographics and the cross-sectional distribution of stock holdings. The AMH does not imply that asset allocation is any less challenging, but it does provide a rationale for the apparent cyclical nature of risk factors and points the way to new research directions in determining investor sentiment.

How does investor sentiment impact the nature of risk premiums across securities? To determine an empirical-based explanatory conclusion, a mean–variance (MV) portfolio is suggested, which is a portfolio of assets that maximises expected return for a specified return variance. In neoclassical asset pricing, where sentiment is zero, the risk premium for each security is based on its return covariance with the return to any risky MV portfolio. Traditionally, risk premiums are decomposed into a fundamental component and a sentiment component which can be loosely interpreted as an abnormal return. The behavioural stochastic discount factor (SDF)-based model can be used to price all assets and to generate the return distribution for an MV-efficient portfolio. The return is a linear function of the SDF, with a negative coefficient. In the model, sentiment impacts both expected returns and risk, as well as the relationship between them, with subsequent implications for asset pricing methods. It is hence dependent upon a continuously time-changing framework.[7]

Blackburn and Ukhov have explored the preferences for skewed returns using various utility functions under the assumption that sentiment is zero.[8] The return to a traditional MV portfolio is approximately the return to a portfolio. The return to a behavioural MV portfolio is more volatile than the return to a traditional MV portfolio consisting of the market portfolio and the risk-free security because the peaks and valleys correspond to exposure from risky arbitrage. Therefore, maximising expected return involves the exploitation of nonzero sentiment. MV returns are very negatively skewed relative to the market portfolio because returns to a behavioural MV portfolio are not only extremely low in low growth states, but fall off quickly as the rate of consumption growth declines. Indeed, in a discussion about MV portfolios, some readers might be surprised that being skewed is an issue at all.

A classic result is that the risk premium can be expressed as the product of the asset's beta with respect to any risky MV portfolio and the risk premium of the MV portfolio. It continues to hold when the MV frontier has a behavioural structure, because it is an equilibrium property, not depending on whether sentiment is zero or nonzero. To understand the implications that the behavioural MV shape has for the nature of risk premiums for individual securities, it is worth considering what the systematic risk entails. Securities with returns highly correlated with the returns to an MV portfolio will be associated with high degrees of systematic risk and feature being negatively skewed relative to the market portfolio.

Market efficiency and zero market sentiment go hand in hand. When market sentiment is zero, the market probability density function is objectively correct, and all assets are priced efficiently. However, if market sentiment is nonzero, some assets are mispriced.

From this point forward, the paper denotes the market fundamentals M and a sentiment component of the risk premium $\Lambda$. i is the gross risk-free rate. Fundamental variables are aggregate consumption growth g, the market coefficient of relative risk aversion $\gamma$M and the market time discount factor $\delta$M.

The risk premium parameter associated with an asset's return distribution r is based on the function:

$$i(1 - h)/h \tag{1}$$

Expecting in h taken with respect to $\Pi$,

$$h = E(\delta \exp(\Lambda)\ g - \gamma\ r) \ /\ E(\delta\ g - \gamma\ r) \tag{2}$$

When the market is efficient, $\Lambda = 0$, $\exp(\Lambda) = 1$ and therefore $h = 1$. In this case, the abnormal return component must be $i(1 - h)/h = 0$.

When all investors share the same coefficient of relative risk aversion and time discount factor, $\gamma M$ and $\delta M$ are equal to these respective shared values. When market parameters are heterogenic, the market values are equilibrium aggregates. It thus follows that the equation relating the log-SDF and sentiment has the form:

$$\ln(m) = \ln(\delta M) - \gamma M \ln(g) + \Lambda \quad (3)$$

In the traditional neoclassical framework, market sentiment is zero, and ln(m) is just $\ln(\delta M) - \gamma M \ln(g)$. Figure 1 contrasts a traditional neoclassical SDF scenario based on fundamentals alone with a behavioural SDF that reflects the sentiment function. The difference between the two functions is driven by sentiment $\Lambda$.

Sentiment is actually composed of both a direct effect and an indirect effect stemming from the investors' sentiment; market sentiment $\Lambda(\omega t)$ is defined as the sum of three log-ratios: $PM(\omega t)/\Pi(\omega t)$, with the numerator being the market probability density function, and the denominator being the value that this function would take if the sentiment of all investors were zero. The other ratios are similarly defined as $1/\gamma M$, which captures the direct effect, and $\delta M(t)$, used to express the indirect effect. Then, the market sentiment function holds the form $\Lambda(\omega t) = \ln(PM(\omega t)/\Pi(\omega t)) + \ln(\gamma M(\omega t)/\gamma\Pi(\omega t)) + n(\delta M(t)/\delta\Pi(t))$.

The neoclassical SDF only reflects the fundamental component of risk, whereas the behavioural SDF adds the sentiment component.

In this respect, the sentiment function is the difference between the logarithms of the behavioural SDF and the traditional neoclassical SDF. Blackburn and Ukhov[8] use Jackwerth's findings[9] to estimate absolute risk aversion Q'/Q – P'/P, where Q denotes the market probability density and P denotes the associated risk-neutral density. Their estimation uses an estimate of $\Pi$ for Q, thereby implicitly treating sentiment as zero. However, market prices are based on the PM beliefs of the representative

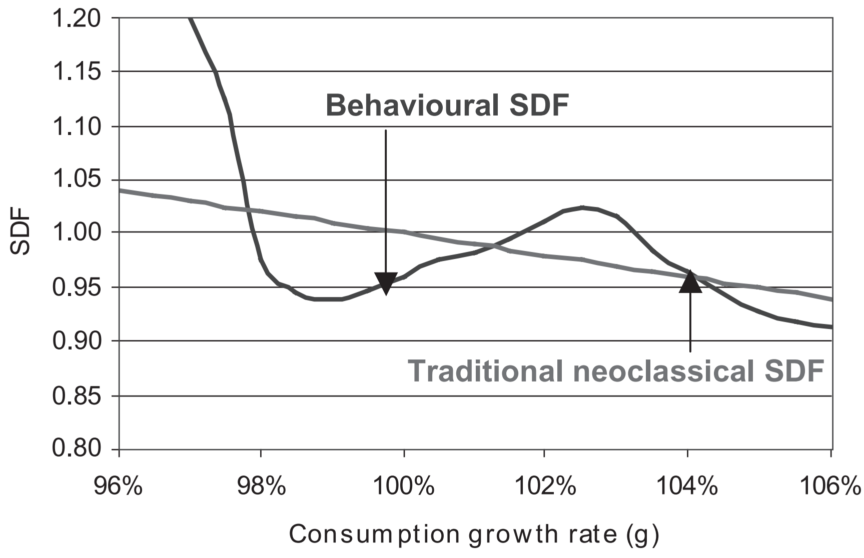


**Figure 1:** Comparison of behavioural SDF and traditional neoclassical SDF

investor, which only equals $\Pi$ when sentiment is zero. Equation (3) holds PM $= \Pi$ (PM/$\Pi$) to incorporate sentiment and substitute this expression of PM for Q in Q'/Q – P'/P. Using power utility to write the expression for absolute risk aversion enables $\Lambda \approx$ PM/$\Pi$ to be solved in terms of $\gamma$.

Harvey and Siddique study the cross-section of stock returns using 'co-skewness' relative to the market portfolio.[10] Co-skewness can be defined as the beta of a security's return relative to the squared market return. It measures the amount of MV skewness that a security adds to a 'well diversified' portfolio. It is appropriate when the SDF has a quadratic-like U-shape and plays a role analogous to beta in the capital asset pricing model (CAPM). Notably, there is a negative premium to holding stocks with returns that exhibit positive co-skewness relative to the market portfolio. The authors point out that the market factor by itself explains only 3.5 per cent of cross-sectional returns. However, the combination of the market factor and co-skewness explains 68.1 per cent of cross-sectional returns. This value rivals the 71.8 per cent associated with the use of the market factor, size and book-to-market equity. For momentum, recent winners feature lower co-skewness than recent losers.

One can deduce that much of the explanatory power of size, book-to-market equity and momentum in the returns of individual stocks plausibly derives from co-skewness. Dittmar has developed a flexible nonlinear pricing kernel approach in the tradition of a zero sentiment representative investor model.[11] The empirical SDF in his analysis does not decrease over its range in a monotone manner, but instead has a U-shaped pattern. In addition to sentiment, a preference for positive skewness might also contribute to the low premium associated with positively-skewed stocks. That is, investors who favour positively-skewed return patterns, such as long shots at the race track or payoffs from lottery tickets, overweight the probability density of high returns as if they were unrealistically optimistic. Kumar uses the term 'lottery stocks' to describe such stocks that share similar properties to lottery tickets, that is, a small probability of a high reward, but a negative expected payoff.[12] Lottery stocks feature high variance and positive skewness. Kumar finds that both individual investors and institutional investors hold more lottery stocks than chance alone would predict. Those who favour lottery stocks underperform other investors by 5.9 per cent a year on a risk-adjusted basis.

Attempts to estimate the market's aversion to risk have produced puzzling results. Jackwerth[9] and Rosenberg and Engle[13] have both estimated the coefficient of absolute risk aversion for the market in the case when sentiment is (implicitly) zero. These studies find extreme coefficients of risk aversion for the market. Reasonable benchmark values for the coefficient of relative risk aversion (CRRA) involve the range 1.5 to 3.5, with a few outliers between 0 and 1 and between 5 and 6.5. The Rosenberg-Engle estimated range for the CRRA is 2 to 12, with a mean of 7.6, finding that market risk aversion is highly variable over time. Jackwerth's estimates imply that the market's coefficient of CRRA ranges between –14 and 27.[9] Negative values, which indicate risk seeking, are especially surprising, but one may note that the shape of the absolute risk aversion function which Jackwerth derives for the market is not time invariant or monotone in its declining, as traditional theory would suggest. Instead, it mostly tends to be time varying and U-shaped.

The culprit in these risk-aversion estimation exercises is the assumption that sentiment is zero. If sentiment is nonzero in practice, then assuming it to be zero forces the risk aversion parameters of the model to pick up the effects of sentiment in the market: these are mostly upward-sloping sentiment shapes that conform to unrealistic optimism.

Asset managers should draw their inspiration from Scheinkman and Xiong,[14] who assume that the aggregate consumption growth rate follows a mean-reverting diffusion process with a time-varying stochastic drift. Investors do not observe the drift directly. Instead they receive a noisy signal with change equal to the sum of drift plus a noise term that is uncorrelated with the change in drift. They then make forecasts of the change in drift. However, some of them overreact to their forecast errors in respect of the rate of change in the signal. In this respect, they read more into their signal forecast errors than is appropriate because they believe that the noisy signal features a positive correlation with the change in drift. As a result, they overweight the contribution of their signal forecast errors when predicting how the drift term will subsequently change. This overweighting leads them to underestimate the drift volatility, thereby leading to overconfidence on their part.

However, the SDF-based model with power utility must also focus on the impact of heterogeneity on asset pricing, as the degree of dispersion can be treated as a risk factor, alongside the Fama-French factors and momentum. The implications on asset pricing must be investigated in a continuous time framework and feature the Hölder average property for PM when investors have power utility functions.[9] The heterogeneity introduces a bias into asset pricing through the time discount factor associated with utility. Ben Mansour *et al*. demonstrate how the extent of this bias depends on the degree of dispersion among investors' beliefs:[15] pessimistic sentiment emerges as an aggregate of the pessimistic beliefs of individual investors and causes a higher market price of risk and a lower risk-free rate. There is then little doubt that a positive correlation between risk tolerance and pessimism induces a higher market price of risk. This well-grounded empirical conclusion underlines the necessity of assessing the market risk through a time-varying, diffusion volatility and jump component.

In this sense, Bakshi and Wu previously examined an important behavioural issue ie irrational exuberance estimating a neoclassical SDF-based equation by combining return distribution estimates based on historical data with risk-neutral density information inferred from option prices.[16] Their neoclassical interpretation of a negative risk premium is risk-seeking preferences. They found that the risk–return relationship was different during the NASDAQ bubble of 1999–2000. Outside the bubble period, all risk premium components were positive. During the bubble period, the risk premium components for both time-varying volatility and diffusion became negative. Additionally, open interest and trading volume for index options suggest that investors became increasingly concerned about a crash during the bubble period.

If Bakshi and Wu do not estimate sentiment directly, irrational exuberance in the presence of risk must be considered as it causes the violation of the expected utility and the Bayes updating. The Siberian stock market was a modest but flourishing, competitive regional market. Interestingly, for the past six years, with four exceptions, stocks have risen every Wednesday and fallen every Thursday. Furthermore, over the past six years, on all but three weekends in which the returns were modest, stocks opened lower on Monday than they closed on Friday. Investor sentiment is correlated across investors and random, which forces prices to differ from fundamentals. (An exception, closed-end funds are traded at discounts from net asset value. They are a function of investor sentiment, correlated across investors, implying that discounts are correlated across funds, and arbitrage is costly and problematic. Managers fight opening up their funds and fight takeovers, while correlated investor sentiment makes arbitrage risky; discounts could widen instead of tending to a premium.)

It is plausible that many investors attribute higher return to the timing skills of practitioners and not to the greater risk. This consideration may be particularly important when one asks whether individuals change their own investment strategies that have just earned them a high return. When people imitate investment strategies, they appear to focus on standard metrics such as returns relative to market averages, and do not correct for *ex ante* risk. As long as enough investors use the pseudo-signal of realised returns to choose their own strategy, noise traders will persist. Therefore, a large fraction of market movements cannot be attributed to news about future dividends and discount rates.

Such excess volatility becomes even easier to explain if one relaxes the assumption that all market participants are either noise traders or sophisticated investors who bet against them. A more reasonable assumption is that many traders pursue passive strategies — neither responding to noise nor betting against noise traders. If a large fraction of investors allocate a constant share of their wealth to stocks, then even a small measure of noise traders can have a large impact on prices. More generally, the increasing availability of financial market data at intraday frequencies has not only led to the development of improved ex-post volatility measurements (eg VIX, VXN, VXD, which track the S&P 500, the NASDAQ 100 and the Dow Jones Industrial Average, respectively), but has also inspired research into their potential value as an information source for longer-horizon volatility forecasts.

Empirical researchers have stated that the volatility of sentiment often rises in a speculative episode. Here, the paper follows the suggestion of Baker and Wurgler, which states that the relative influence of fundamentals and sentiment on aggregate market returns changes.[17] The optimal strategy for an individual investor would be a market timing strategy that calls for increased exposure to stocks after they have fallen and decreased exposure to stocks after they have risen in price. It requires investment in the market at times when noise traders are bearish, in anticipation that their sentiment will recover. However, successful pursuit of this strategy can require a long time horizon, and is by no means safe because of the noise trader risk that must be run; arbitrageurs can take advantage of mean reversion in noise traders' beliefs. An alternative would be to gather information about future noise trader demand shifts, and to trade in anticipation of such shifts. With short horizons, it may well be more attractive for smart money to pursue these anticipatory strategies than to wait for the reversion of noise traders' beliefs to their mean.

Moreover, both optimistic and pessimistic individuals with anticipatory feeling and ex-post disappointment often select a portfolio which is less risky. This stands in contrast to the optimal expectations theory in which individuals are always optimistic and select a riskier portfolio, reinforcing the equity premium puzzle. In this way, institutional investors are found to forecast future stock returns correctly if noise trader and fundamental risk is fixed. This does not necessarily mean that their forecasts are always correct. It rather verifies that, on average and net of unpredictable factors, institutional sentiment gets the direction of future stock market movement right. This fits well for the assumption of institutions as rational arbitrageurs who collect and aggregate fundamental information as their sentiment contains information beyond that of several fundamental risk factors alone. Table 1 presents the risk taxonomy faced by an arbitrageur engaged in long short stocks trading.

Rising individual sentiment has a negative effect on future stock returns and vice versa. This stands in line with the hypothesis that excessive optimism (pessimism) of noise traders drives prices above (below) fundamental values. This causes a subsequent reversal to intrinsic values so that individual sentiment and expected returns are indeed negatively related.

Both traders and asset managers should rebalance their portfolio around the concept of a stochastic discount factor. A well-defined notion of sentiment lies at the heart of its behavioural version based on the percentage error in probability density, both at the level of the individual investor and the market level. Sentiment manifests itself in the pricing of all assets through the SDF. A proxy is the difference between two SDFs, one neoclassical and the other freely fit. The determinants of market sentiment are time-dependent; investors' tactical asset allocation and relative wealth typically vary over time, adjusting the SDF value.

Behavioural asset pricing theory features MV portfolios the returns of which are negatively skewed relative to the squared return of the market portfolio, offering a basic explanation of

**Table 1:** Taxonomy of risks inherent to an investor trading long short stocks

| | Fundamental risk | Noise trader risk |
|---|---|---|
| Systematic risk | Hedged – non-diversifiable | Non-hedged – non-diversifiable |
| Firm-specific risk | Hedged – diversifiable | Non-hedged – diversifiable |

why assets exhibiting positive co-skewness are associated with lower-risk premiums than assets exhibiting negative co-skewness.

This paper has proposed a static market sentiment function associated with individual securities experiencing MV returns. Future work will consist of testing its dynamic evolution under the hypothesis that the sentiment function will change over time. Behavioural finance may be no longer as controversial a subject as it once was. Its widest application is set in the futures and options market, which is very large and growing quickly. Derivatives are the natural vehicles to exploit the various pockets of inefficiency associated with the projections of nonzero sentiment functions onto individual stocks.

More generally, investment managers should incorporate as much 'behaviour' into asset allocation models but not look back at the financial articles published in the past 20 years. Psychology offers too many answers: are people optimists or pessimists? They are both. Neoclassical theory predicts the magnitude as well as the signs of effects. This paper recommends the assumption of correlated individual irrational behaviour: psychology is too often a grab-bag of fascinating anecdotes and observations begging for theory. When added to inoperability and inefficiency, it has little to offer for price determination. After all, to do otherwise would not be irrational.

The investor sentiment approach is challenging from a practitioner viewpoint: characterising and measuring uninformed demand or investor sentiment, in other words understanding the foundations and volatility in investor sentiment over time; and determining which stocks attract speculators and/or offer arbitrage potential. Further empirical research into this perspective is required: the potential payoffs are substantial for improving fundamental market beta proxies. In directly affecting the equity premium and the cost of capital, investor sentiment may be positively considered as a floating but quantifiable market risk parameter. Finally, it would open the way to a more sensible allocation of corporate investment capital across safer and more speculative firms.

## ACKNOWLEDGMENT

David Koenig is thanked for his advice and encouragement. Thanks are also due to Professor Christophe Villa, Audencia School of Management, for his insightful suggestions that have substantially improved the paper.

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