The Implications of Behavioural Finance for the Modelling of Securities Prices

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Abstract

Much of the traditional economic and financial modelling is based on the assumption that individuals act *rationally*, processing *all* available information in their decision-making process. However, research conducted on the ways that human beings arrive at decisions and choices when faced with uncertainty has uncovered that this is not precisely the case. People often make systematic errors, the so-called *cognitive biases*, which lead them to less rational behaviour than the classical economic paradigm assumes. These cognitive biases have been found to be responsible for various irregular phenomena often observed in financial markets (turbulence, predictable trends, seasonable cycles, "bubbles", etc). Behavioural finance attempts to merge concepts from financial economics and cognitive psychology in an attempt to better understand how the systematic biases in the decision-making process of financial agents influence prices and other dimensions of financial markets. This paper reviews some results from the behavioural finance or related literature. We argue that the findings of behavioural finance often suggest a new approach to the modelling of securities prices and other financial phenomena.

Keywords: behavioural finance, modelling of securities prices, cognitive biases.

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1 Introduction

Much of the economic and financial theory is based on the notion that individuals act rationally and consider all available information in the decision-making process. However, researchers have uncovered a surprisingly large amount of evidence that this is frequently not the case. Many examples of irrational behavior and repeated errors in judgement have been documented in academic studies, the most influential of them being Kahneman and Tversky's papers on judgemental heuristics and biases judgement [37] and on prospect theory [22], a framework for choice under uncertainty.

The field of "behavioral finance" is essentially the application of these ideas in finance. It deals with understanding and explaining how certain cognitive errors or *biases* influence investors in their decision-making process. The proponents of this approach suggest that such biases are often responsible for various irregular phenomena that appear in financial markets (turbulence, predictable trends, seasonable cycles, "bubbles", etc). Using results from cognitive psychology, behavioural finance attempts to shed more light on the nature of these financial "anomalies".

In this paper, we review several results from the behavioural finance literature in an attempt to shed light on the question: what do the merits of behavioural finance suggest on the types of input variables that a financial modelling framework should take into account? We believe that such a question is of great importance to quantitative financial analysts. In the last twenty years several radical psychology-oriented theories made their appearance in the financial world, which have significantly changed the way we see financial prices. Those theories in many senses contradict the traditional financial framework, where a security analysis is solely based on *fundamental* information, i.e information concerning the company, the sector or the economy as a whole. It is our belief that incorporating "behavioural" ideas in the modelling framework definitely leads to more realistic and successful representations of financial phenomena, such as securities prices.

The rest of the paper is organised as follows: In section 2 we review both theoretical facts and empirical evidence concerning the behaviour of securities prices in financial markets. Section 2.1 presents the idea of efficient markets, one of the most debated hypothesis in finance. Over the last thirty years, plenty of empirical studies on individual stocks or the aggregate stock market revealed phenomena of seasonability or predictability that contradict the efficient markets hypothesis. Those phenomena are often referred to as financial "anomalies", since they can hardly been explained by economic theories assuming rational agents. Several of the widely acceptable irregularities are reviewed in section 2.2. Section 3 provides an overview of behavioural finance literature. Our exposition of the topic is concentrated around two building blocks: the proposition of limited arbitrage (section 3.1) and experimental evidence concerning investors' psychology (section 3.2). In section 3.3 we give several explanations of the financial anomalies that have been proposed in the behavioural finance literature. The thesis of this paper is that the findings of behavioural finance suggest a radical approach to the modelling of financial prices, which is usually in contrast to the traditional fundamental analysis. Several of the ingredients of the modelling philosophy are discussed in section 4. Finally, section 5 proposes an alternative framework for modelling financial prices that summarises the ideas discussed in previous sections. Section 6 concludes the paper and discusses possible directions for future research.

2 Empirical evidence on financial prices

2.1 Efficient markets?

In the traditional economic framework where agents are rational and there are no frictions, a securitys price equals its "fundamental value". This is the discounted sum of expected future cash flows[1], where in forming expectations investors correctly incorporate all available information. Fundamental news is the only driving force of security prices. When investors learn something about the fundamental value of securities, they quickly respond to new information by bidding up prices when news are good and bidding down prices when news are bad. All new information is quickly incorporated in prices, leaving thus no space for systematically earning superior (risk-adjusted) returns, based on this information signal. This is, in fact, the *Efficient Markets Hypothesis* (EMH), which was pioneered by Jensen [20], Fama [14], et al.

According to the supporters of EMH, the efficiency of markets does not critically depend on the rationality of all investors. In many scenarios where some of the investors are not rational markets can be still efficient. In one scenario, irrational investors do no communicate with each other and hence their trades are random and uncorrelated. However, due to the large number of such investors the effect of noise trading to the price will tend to disappear in the limit. In one other commonly discussed case, irrational investors make common errors, possibly due to some kind of herding behaviour, and thus have correlated trades. The argument here, originally introduced by Friedman [16] and Fama [13], is based on the notion of *arbitrage*.

Genarally speaking, arbitrage is the achievement of riskless profits without capital commitment. Arbitrage strategies usually involve the simultaneous purchase and sell of securities with similar future cash flows traded at different prices. As an "arbitrageur" buys the cheap security and sells the expensive substitute, his net future cash flows will be close to zero and gets his profit up-front. To see how the mechanism of arbitrage can correct the mispricing of an asset, let us assume that some security becomes overpriced in a market relative to its fundamental value and a substitute security is available. Smart investors or arbitrageurs could earn a riskless profit by selling short the expensive security and simultaneously buy the similar one. Due to the competitive activity of a large number of arbitrageurs, the two prices will tend to equalize and, in equilibrium, the overpriced security will be brought back to its fundamental value. Thus, the process of arbitrage, through the activity of rational investors, eliminates the effect of irrational traders, as long as securities have close substitutes.

[1] The rate of discounting is adjusted to the (normatively acceptable) riskiness of the asset.

2.2 Financial "anomalies"

Empirical studies of the behavior of individual stocks or the aggregate stock markets have unearthed several phenomena which are hardly to explain using models where agents are rational and markets are efficient. These facts, often mentioned in the literature as "anomalies" often document that some stocks systematically earn higher average returns than others, although the risk characteristics of such stocks would not prompt for such thing. Among the most widely acceptable facts are:

Excessive Volatility of prices relative to fundamentals. Shiller's [33] work on stock market volatility showed that stock market prices are far from volatile than could be justified by a rational model in which prices are equal to the expected net present value of future dividends. Dividends and other fundamentals simply do not vary enough to rationally justify observed aggregate price movements. This fact was also earlier observed by M. Keynes who mentions that "...day-to-day fluctuations in the profit of existing investments, which are obviously an ephemeral and non-significant characteristic, tend to have an altogether excessive, and even absurd, influence on the market" ([23], pp. 153-154).

Long-term reversals. De Bondt and Thaler [4] provide evidence of long-term reversal of returns in financial markets. They compare the performance of two groups of companies: extreme 'losers', i.e. companies with several years of poor news, and extreme 'winners', i.e. companies with several years of good news. In their study they find that extreme losers (winners) tend to earn on average extremely high (relatively poor) subsequent returns.

Short-term trends (momentum). Jegadeesh and Titman [19] report evidence of short-term trends or momentum in stock market prices. They showed that certain movements in stock prices that persist over a period of six to twelve months are typically followed by future movements in the same direction.

The "size" premium. Historically, stocks issued by small companies have earned higher returns than the ones issues by large companies. Moreover, the superior return to small stocks seems to concentrate in January of each year. It seems that in equilibrium investors impose a size premium on the price of a stock but there is no evidence that using standard measures of risk small stocks are that much riskier in January.

The predictive power of price-scaled ratios. Several company-specific variables, like the book-to-market (B/M) or the earnings-to-price (E/P) ratios, where some measure of fundamentals is scaled by price, have been proven to have predictive power regarding the average return of a stock. In particular, De Bondt and Thaler [5], Fama and French [15] and Lakonishok et al. [25] found evidence that portfolios of companies with low book-to-market ratio have earned sharply lower returns than those with high ratios. The book-to-market ratio is defined as the accounting book value of the company's assets to the market value of its equity. The B/M ratio can be thought as a measure of the cheapness of a stock. Companies with the lowest B/M ratio are relatively the most expensive "growth" ("glamour") firms, whereas the ones with the highest B/M ratio are relatively the cheapest "value" firms. Basu [2] also observed that stocks with extremely high earnings-to-price ratio earn larger risk-adjusted returns than the ones with low earnings-to-price ratio.

The predictive power of corporate events and news. It is often the case that stock prices overreact to corporate announcements or events (earnings or dividents announcements, stock repurchases, equity offerings, etc.). The effect of an announcement or event seems to persist for significant time, creating post-announcement drifts. For instance, as regards earnings announcements, Bernard and Thomas [3] find that stocks with surprisingly good news outperform, in terms of returns, those with surprisingly bad news over a period of 60 days after the announcement takes place. It is often hard to tell a rational "story" for why the premia should be concentrated in this way, given that there is no evidence of changes in systematic risk around earnings announcements.

Reaction to non-information. According to EMH, prices move only in response to fundamental news concerning the company, the sector or the economy as a whole. However, often many sharp moves in stock prices do not appear accompany significant news. Cutler et al. [10] examine the fifty largest one-day stock price movements in the U.S. after World War II and find that many of them came on days of no major announcements. This evidence is broadly consistent with Shiller's [33] finding of excessive volatility of stock returns. Simiral conclusions have been reached by Roll [29, 30], about futures on orange juice and stocks. Overall, it seems that fundamental data are often inadequate to explain the volatility of prices; shocks other than news appear to move prices.

3 Behavioural finance: an overview

3.1 Limited arbitrage

As explained in section 2.1, arbitrage plays a critical role in the analysis of securities markets, because its effect is to bring prices to fundamental values and to keep markets efficient. For this reason behavioural finance attempts to understand how well the above almost "textbook" description of arbitrage approximates reality. One of the major foundations of BF is the hypothesis of *limited arbitrage*, which shows that if irrational traders cause deviations from the fundamental value of an asset, rational traders will often be powerless to do anything about it. This is so because for various reasons opportunities for arbitrage in real-world securities markets are often severely limited. First of all, real-world markets are far from perfect. Several 'frictions' such as transaction costs, margin payments, etc., make it difficult to perfectly replicate an asset. It is also very common the case that many securities do not have fundamentally perfect or often good substitutions. In that case, arbitrageurs run a fundamental risk. Even when good substitution is achievable, there is no warranty that the original source of mispricing, i.e the the trading of noise investors, will not cause further deviations from the fundamental value. Due to the short investment horizon and other restrictions that arbitrageurs are usually faced with, arbitrage becomes a risky activity which perhaps arbitrageurs will not undertake[2].

[2] See [1], section 2, and [36], chapter 1, for an extensive reasoning on limitations to arbitrage.

3.2 Investor's Psychology

The fact that arbitrage is limited helps explain why prices often settle at a level far from fundamental values when perturbed by noisy, irrational traders. However, in order to say more about the structure of these deviations and thus make sharper predictions, one needs to specify the exact form of agents' irrationality. This means how real-world investors actually form their beliefs and valuations, and more generally their demand for assets in real-world markets. For guidance on this, behavioral models typically turn to the extensive experimental evidence compiled by cognitive psychologists on the biases that arise when people form *beliefs* and on peoples *preferences*. This is actually the *investor's psychology* part, the second major building block of behavioral finance.

The following two sections summarize some findings from experimental psychology that may be of relevance to financial economists. Our discussion of each finding is necessarily brief. For a deeper understanding of the phenomena we touch on, we refer the reader to the the edited volume of Kahneman, Slovic and Tversky [21] and the survey of Barberis and Thaler [1].

3.2.1 Beliefs

In contrast to the traditional economic framework, psychology has revealed that when agents form beliefs in practice they are usually subject to several cognitive biases which can be due to heuristics. Heuristics refer to rules of thumb which humans use to made decisions in complex, uncertain environments. There may be good practical reasons for adopting a heuristic, particularly when time available for decision making is limited. However, as it was revealed, heuristic decision processes may result in poorer decision outcomes. Typical examples of biases resulting from the use of heuristics include:

Representativeness – refers to the tendency of decision makers to view events as typical or representative of some specific class, that is to see patterns where perhaps none exists. An important consequence of the representatiness bias for financial markets is that investors tend to assume that recent events will continue in the near future, and therefore seek to buy "hot" stocks and to avoid stocks which have performed poorly in the recent past. As we shall later see, this could be a plausible explanation for overreaction and long-term reversal in security prices.

Overconfidence – investors often tend to overestimate their their "private signal", i.e. information that they have generated on their own, and their ability to predict the market. One possible side effect of this bias is excessive trading[3]. Overconfident investors slowly revise their personal assessments in the

[3] The classical economic equilibrium theory asserts that when agents receive heterogeneous information, they tend to communicate their private signals through purchase and sell orders. In that sense, each investor's order contains useful information about his private signal. Thus, taking the rationality of all agents for granted, it may worth for an investor to revise his private opinion in the light of new information coming from the activity of other investors. This rational revision of expectations leads to a high level of consensus as to the future stock's payoffs and little trading. However, if investors are subject to overconfidence then they only concentrate

face of new public evidence. Interesting, but overconfidence is by no means limited to individual or non-expert investors. There is evidence that professional financial analysts are also reluctant to revise their previous assessments, especially when it comes to evaluating the companys future performance (see [6]).

Anchoring – When people form estimates, they often start with some initial, possibly arbitrary, value and then adjust away from it. However, experimental evidence shows that people often “anchor” too much on their initial estimate and the adjustment is insufficient. On a financial level, this bias often leads investors to expect a share to continue to trade in a predefined range or to expect a company’s earnings to be in line with historical trends. This in turn possibly leads to underreaction to trend changes or fundamental news about the performance of the company.

Gamblers fallacy – arises when people inappropriately predict that a trend will reverse. This tendency may lead investors to anticipate the end of a run of good (or poor) market returns. Gamblers fallacy can be considered to be an pervasive belief in regression to the mean. Sometimes regression to the mean is incorrectly interpreted as implying that, for example, an upward trend must be followed by a downward trend in order to satisfy a law of averages.

3.2.2 Preferences

An essential ingredient of any model trying to understand prices or trading behaviour is an assumption on investor preferences, i.e. on how investors evaluate risky gambles. The vast majority of models assume that investors evaluate gambles according to the Expected Utility (EU) framework, i.e they seek for the alternative that maximises the expected utility of wealth. However, experimental work in the last decades has shown that people systematically violate EU theory when choosing among risky gambles. In response to this, there has been an explosive work of the so-called non-EU theories, the most promising for financial application being the Prospect Theory.

Prospect Theory proposes a purely descriptive framework for the way people make decisions under conditions of risk and uncertainty, which is far richer in behavioural elements than EU theory. The key concepts addressed by the theory include:

- *Loss aversion* – In Prospect Theory utility is defined over gains and losses rather than over final wealth. This fits naturally with the way gambles are often presented and discussed in everyday life. Individuals often show greater sensitivity to losses than to gains, i.e. the “mental” penalty they associate with a given loss is greater than the “mental” reward from a gain of the same size [22]. This is often referred to as *loss aversion*, and shows that investors may be reluctant to realise losses. Loss aversion need not imply that investors in the real-world are consistent

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on their own signal, even if that of other investors is different. This bias-driven behaviour leads to inadequate revision of opinions and excessive trading (large trading volume).

in their attitude to risk, for example risk-averse as the classical economic framework assumes. There is evidence that people play safe when protecting gains but are willing to take chances in an attempt to escape from a losing position.

- *Regret aversion* – arises because of people's desire to avoid feeling the pain of regret resulting from a poor (investment) decision. Regret aversion embodies more than just the pain of financial loss. It includes the pain of feeling responsible for the decision which gave rise to the loss. This aversion may encourage investors to hold poorly performing shares, as avoiding their sale also avoids the recognition of the associated loss. The wish to avoid regret may bias new investment decisions of investors, as they may be less willing to invest new sums in stocks that have performed poorly in the recent past. As Koening [24] suggests, the wish to avoid regret may encourage investors' herding behaviour, for example to invest in "respected companies", as these investments carry implicit insurance against regret.

- *Mental accounting* – there are numerous demonstrations of a shift in preferences of a decision-maker depending on the framing of the problem. Framing refers to the way that a problem is posed for the decision-maker. No normative theory of choice can accommodate such behaviour, since a fundamental principle of rationality is that choices should not depend on the description of the problem. In many actual choice contexts, the decision-maker has the flexibility in how to think about the problem. The process by which decision-makers formulate problems for themselves is called *mental accounting*. One important implication of mental accounting is *narrow framing*, i.e. the tendency to treat individual gambles separately from other portions of wealth. In that sense, investors tend to treat each element of their investment portfolio separately. This can lead to inefficient decision making. Investors may be less willing to sell a losing investment because its "account" is showing a loss. Another aspect of mental accounting relates to observations that people vary in their attitudes to risk between their mental accounts. Investors may be risk averse in their downside protection accounts and risk seeking in their more speculative accounts.

Prospect theory, at least in its initial version, deals with gambles with known objective probabilities. However, in reality, the actual probabilities of scenarios are hardly known and decision-makers often use their own subjective probability distribution to express the likelihood of occurrence of each scenario. To handle these situations, Savage [32] has developed the *Subjective Expected Utility* (SEU) theory, which suggests that, under certain axioms, preferences can be represented by the expectation of a utility function, where the expectation is taken with respect to the individual's *subjective* probability assessment. Still, experimental evidence in the last decades has been unkind to SEU as it was to EU theory. People tend to dislike situations or gambles where they are uncertain about the probability distribution of the scenarios. Such gambles are often termed as *gambles of ambiguity* and the general dislike for them as *ambiguity aversion*. Heath and Tversky [18] argue that in the real world, ambiguity aversion has much to do with how competent an individual feels he is at assessing the relevant distribution. Further evidence that supports the competence hypothesis is that in situations where people feel especially competent in evaluating a gamble, the opposite of ambiguity aversion, namely a "*preference* *for the familiar*", is observed.

3.3 The behavioural approach to financial "anomalies"

According to the behaviour approach, many of the anomalies described above can be plausibly explained if we accept that investors occasionally under- or overreaction to information. The underreaction part shows that security prices underreact to fundamental news, such as earnings announcements. If the news is good, prices keep trending up after the initial positive reaction; if the news is bad, prices keep trending down after the initial negative reaction. Put differently, current news has the power in predicting not just the returns on the announcement of these news, but also returns in the future, when the news is already stale. The momentum evidence described before is consistent underreaction, since the short-horizon trend in returns may reflect slow incorporation of news into stock prices.

The overreaction hypothesis shows that security prices overreact to consistent patterns of news pointing in the same direction. Securities that have had a long record of good news tend to become overpriced and have low average returns afterwards. Securities with a row of good performance, however measured, receive extremely high valuations, and these valuations, on average, return to mean. Both long-term reversals and the predictability of returns from accounting ratios (B/M, E/P, etc) are closely related to overreaction.

DeBondt and Thaler [4] argued that because investors are subject to the representativeness heuristic, they become overly optimistic about past "winners" and overly pessimistic about past "losers", which leads to long-term reversals. This many be the case because extreme "losers" are companies with several years of poor news, which investors extrapolate into the future leading to an undervaluation of the firms. As extreme "losers" have become too cheap they bounce back as investors gradually revise their opinions. On the other hand, extreme "winners" are companies with several years of good news, inviting thus temporary overvaluation and subsequent reversal.

Daniel, Hirshleifer and Subrahmanyam [11] provide another explanation for the long-run negative autocorrelation in stock returns based on the overconfidence bias. According to their view, this bias may as well explain the 'excessive volatility' anomaly. The authors argue that investors or analysts typically generate information for trading though various means (analysing financial statements, verifying rumors, interviewing management, etc.) that they later juxtapose against publicly available information. Overconfident investors initially put too much weight on their private "signal" relative to public information and this causes the stock price to overreact. "On subsequent days, as more public information arrives, the price, on average, moves still closer to the full-information value" ([11], p. 1841).

Interpretations of the post-announcement drifts have been based on the conservatism and representativeness bias. Shleifer [35] supports that when investors receive news about a company (e.g. earnings news), they tend not to react to this news in updating their beliefs about the company. This behaviour gives rise to underreaction of prices to corporate announcements and to short horizon trends. At the same time when investors are repeatedly hit with similar news - e.g. good earnings surprises - they not only give up their old model but, because of representativeness, attach themselves to a new model which is consistent with the pattern of news. In doing so, they underestimate the likelihood that the past few surprises are the result of chance rather than of a new regime. This gives rise to overreaction. Overconfidence may as well lead analysts not to adjust their earnings estimates sufficiently when surprises occur (see [6]). This could lead to subsequent price adjustments as analysts revise their incorrect estimates.

Basu [2] offered a bahavioural explanation for the ‘earnings-to-price’ anomaly, which is related to the investors representativeness heuristic. Companies with very high E/P ratio are thought to be temporarily undervalued because investors become excessively pessimistic after a series of bad earnings reports or other bad news, and rush to project their estimates in the future. Once future earnings turn out to become better than the unreasonably “gloomy” forecasts, the price adjusts. Similarly, the equity of companies with very low E/P is thought to be overvalued, before falling in price.

4 Implications of behavioural finance for quantitative modelling

So far, the contribution of behavioural finance (BF) has been to uncover many of the anomalies, mentioned in section 2.2, and provide explanations based on limits to arbitrage or investors’ psychology. The arguments of BF have also found experimental validation though a series of papers which consider economies with two types of traders: the rational and irrational ones, the latter being subject to one or more of the cognitive biases mentioned in section 3.2 (representativeness, overconfidence, etc.). The majority of these works typically reach with two important conclusions: a) the interaction of the two groups of traders produces many of the documented anomalies and b) noise traders eventually survive through the process of “economic selection”, contrary to what Friedman and other classicists have supported. This means that irrationality can have a substantial and long-lived impact on prices.

The above conclusion gives an important message to financial modellers. Common practice in finance is to analyse securities prices in terms of their sensitivity to certain fundamental risk factors, which they are thought to have an influence either directly on the stock price or on the company itself[4]. It is reasonable to think that particular groups of stocks move together because their holders are exposed to common risk factors. The important lesson of BF is that comovement may indeed be evidence of common risk exposure, but such risk does *not* always have to be fundamental. The arguments presented in the limits to arbitrage section suggest that once a collective shift of opinions starts, it is difficult and risky to be eliminated and it thus constitutes an important additional risk factor. Noise trading risk affects more than a particular stock and due to several limitation of arbitrage cannot de diversified away by smart investors. In that sense, it should be treated as a *systematic* and not idiosyncratic

[4] This is actually the idea behind the *Capital Asset Pricing Model* and the *Arbitrage Pricing Theory*, in which the average security’s return is given as a weighted linear combination of a set of determinant factors. Each weight represents the exposure or sensitivity of the security’s return to the particular factor (cf. [12]).

(firm-specific) source of risk. If market professionals are also aware of this fact, then it is very likely that they impose a premium due to noise trading risk. Hence, in that case the comovement of certain securities points to their exposure to common noise trader risk in addition to fundamental risk. This is in particular true, in the case of price divergences between fundamentally identical assets.

BF has indeed uncovered an important risk factor, i.e. noise trading, which is believed to be the cause for various anomalies. The next important step is to test whether apart from the theoretical justification, noise trading follows persistent and predictable patterns. If such patterns do exist, there may be scope for models to detect them and help financial experts exploit the resulting pricing anomalies. Apart from the classic econometric approach where one finds hidden relations between price movements and fundamental data (company's earnings, market index, prevailing interest rates, etc.), it would be relevant to include in the modelling framework more behavioural explanatory variables that capture the effect of noise trading. Models with such behavioural explanatory variables are very likely to outperform traditional financial models. To our knowledge, there has been so far no standard framework on how to incorporate the varying strands of behavioural finance. The common view is that we do need more empirical research of the patterns according to which noise trading makes its appearance in the market.

Although the above discussion suggests that noise trading is a systematic risk factor, still one should bear in mind that it does not have a persistent effect on security prices. Investors' attitude usually changes with time; on some occasions people act rationally and on some others they not[5]. If this is the case then one expects periods when noise trading has a significant influence on price formation and periods when not. Such periods usually have unequal length and appear at irregular moments, often with gradual regime transitions[6]. One interesting area of research is to find models that capture the mechanism of regime changes, i.e. the special circumstances under which noise regimes makes their appearance. An important contribution towards this direction is van den Bergh et al.'s series of papers [39], who apply an artificial intelligence method, called *fuzzy exception learning* algorithm, to detect gradual regime transitions[7].

The important thing about regime shifts is that they point to certain types of explanatory variables that could be included in the modelling framework. During noise trading periods, one expects that financial returns show certain predictable patterns, but during less noisy periods financial markets are more likely

[5] This may be also attributed to *herding behaviour*, typical of non-expert investors. As Shiller [34] claims, noise traders tend to behave socially and follow each others' mistakes by listening to rumors or imitating their neighbors.

[6] The exact timing of regime changes depends on periodic shifts of noise investors' tastes. However, the response of smart-experienced investors against noise trading plays also an important role on the regime transition. Sometimes, arbitrageurs may find it more profitable to trade in a way that corrects mispricing and brings prices back to fundamentals. There is, however, evidence that occasionally, if not often, arbitrageurs "ride on the trend", i.e. follow the direction of noise traders overreaction, in order to make profit ([31], ch. 8).

[7] The idea of the methodology proposed in [38, 39] is to observe the average behavior of system outputs and track deviations from this average behavior. These deviations are then correlated to regions within the system's input space. The output of the method is a set of IF-THEN rules that are able to describe such regimes shifts.

to exhibit the usual "noise-" or random-like behavior, predicted by the Efficient Markets Hypothesis. Hence, over "turbulent" periods one expects behavioural variables to have more explanatory power than fundamental ones. The contrary should be true at times where financial markets follow fundamental news.

5 A financial modelling framework for intelligent methodologies

The ideas discussed in the previous section naturally point to a new modelling approach to describing securities prices. This is schematically depicted in figure 1, at the end of the paper. Perhaps, the diagram presented in figure 1 is more applicable to models of *econometric* style, which essentially use a set of explanatory variables to predict or describe another target variable(s). Both explanatory and target variables usually have the form of *aggregates* or macro-variables, such as security prices, interests, market indices, etc., which in some sense capture the total effect of individual investment decisions of a large number of market agents. An alternative modelling philosophy, often found in the financial literature, is the *multi-agent market models* in which one looks at the underlying structure of the market (individual investment decisions, buying/selling orders, aggregate market supply/demand) in order to predict security prices[8]. Our claim is that the modelling framework proposed in figure 1 could also accommodate this modelling approach with some minor modifications. However, for the shake of simplicity we restrict our attention to econometric models.

The essence of econometric modelling is to find a model that adequately approximates the data-generating process of the target variable:

$$y = \phi(x_1, x_2, ..., x_n) + \varepsilon \tag{5.1}$$

where y is the target variable and $x_1, x_2, ..., x_n$ are the determinant factors of y. ε denotes the "noisy" part of y which cannot be predicted by the explanatory variables (i.e. $\mathbb{E}(\varepsilon|x_1, x_2, ..., x_n = 0)$) and can be due to other non-systematic influences. ϕ is a hidden, typically non-linear, function of the explanatory variables, which can be viewed as the conditional expectation of y given $x_1, x_2, ..., x_n$ ($\mathbb{E}(y|x_1, x_2, ..., x_n)$). Many of the forecasting of prediction problems in finance fall in the framework suggested by (5.1), but as an illustrative case let us consider a typical problem that investors are faced with, the modelling of *equity premium.* In this case y represents the next-period return of a stock and $x_1, x_2, ..., x_n$ are variables that are thought to have a significant effect on the return. Those could be

[8] Several interesting multi-agent market models have been proposed by both the statistical and the artificial intelligence community. See the survey papers [8, 26] for reviews of classical multi-agent models as well as [9, 17, 27, 28] for examples of artificial multi-agent markets that incorporate some form of computational intelligence. [27, 28], in particular, present the well-known Santa Fe Artificial Stock Market, which uses genetic algorithms for the exploration and evolution of agents' trading strategies.

any of the fundamental data of the company (previous-period earnings, dividends) or market/economy data (sector index, trading volume, interest rates, etc.).

As figure 1 suggests, an integral part of the econometric modelling is the selection of the appropriate financial data and an initial filtering method to reduce the unnecessary noise. At this stage, both good domain knowledge and the adoption of advanced statistical/intelligent methods to filter out the noise, inherent in financial data, are of great importance. These two initial stages are amongst the most crucial steps of the modelling procedure and, of course, there is much to be said here. But as these issues have been covered in more detail in other works, we focus on the next stages of the diagram depicted in figure 1.

It is worth noting that most modelling approaches typically jump from the filtering stage directly to the end of the diagram, which is the formation of the model. However, our thesis is that they miss an important ingredient that may increase the effectiveness of the modelling procedure, i.e. the detection of market regimes. The regime detection has important implications on the type of explanatory variables to be incorporated in the final model. Over "turbulent" periods the effect of noise trading is more significant and hence one expects many "anomalies" to make their appearance. Hence, given that a noisy regime has been detected, a behavioural analysis of the stock price dynamics makes more relevance. As we discussed in the previous section, this mainly consists in the detection of certain predictive patterns that anomalies give birth to as well as other variables which somehow capture investors' sentiment[9].

Contrary to what turbulent periods imply for the determinants of securities prices, under normal conditions prices' dynamics is supposed to be in course with the fundamentals. Thus, once a normal regime is decided upon, a fundamental analysis of the stock may be of higher predictive power. In such case certain variables, like earnings-to-price, sector/stock market indexes, prevailing interest rates, etc., which relate to the company, the sector, the market or the economy as whole, should form an integral part of the modelling.

For reasons pointed out in the previous section, there are no abrupt transitions between the two regimes (normal and noisy one) and hence no clear-cut rules as to which explanatory variables to use in each case. What this basically suggests is that the analysis of the stock price return be viewed as a *"fuzzy" classification problem*. In this context, a particular stock prices realisation belongs to both regimes, normal or turbulent one, with different degrees of membership. Allowing the membership in the two regimes to vary, one accounts for a "mixturing" of both types of explanatory variables (fundamental and behavioural ones) in the final model.

Once the type of explanatory variables has been decided, one has to undertake several additional steps in order to identify the best model. Their essence mainly lies in the requirement for the specification of a robust econometric model with high predictive power. Two stages of model specification testing

[9] See footnote 3 on page 6 for a discussion on the relationship between trading volume and investors' over-confidence.

are often followed: *model adequacy tests* and *explanatory variable significance tests*.

The purpose of the first type of diagnostic (model adequacy) is to ensure that our model adequately approximates the hidden deterministic part, $\phi(x_1, x_2, ..., x_n)$, of the data-generating process (5.1). From a model that passes the adequacy tests ones expects that the prediction error term, i.e. the difference between the actual y and the predicted by the model $\hat{y}$, is of purely stochastic nature. The existence of systematic patterns in the error term indicates some model *specification bias*, since, for instance, the model may be of inadequate complexity or some relevant explanatory variables were omitted at the data selection stage.

The second type of diagnostics (explanatory variable significance) concerns evaluating the statistical significance of the explanatory variables in the model. It is quite common in financial applications to include in the model any explanatory variable that is suspected to have any relationship with the target variable, especially when little expert guidance exists. However, for large numbers of explanatory variables models are difficult to use or interpret and the danger of "overfitting" the data becomes considerable. The main trend in econometric modelling is to identify models with the least possible number of independent variables, enough to capture the salient features or "driving forces" of the data-generating process, relegating all minor and random influences to the noise term. This is the well-known principle of *parsimony*, often stated in classical econometrics books (see for example [7]).

6 Conclusions

The purpose of this paper is to introduce non-expert readers to the concepts of behavioural finance, a recently emerged discipline that has radically changed the way we interpret financial phenomena. Behavioural finance provides solid theoretical and empirical foundations for many of the irregularities that are often observed in financial markets and, in many senses, suggests a shift from the classical economic approach to the analysis and modelling of securities prices. The big success of behavioural finance is in stretching the role of noise trading in the determination of securities prices, and in particular the predictable trends or seasonable cycles that it often gives rise to. This finding is of great importance from a quantitative analyst's point of view: apart from the traditional fundamental analysis, the addition of systematic predictable patterns and other behavioural variables can increase the accuracy and representation power of the final model as regards the various financial phenomena. The paper provides an alternative modelling framework that summarises many of the ideas discussed above. At this stage, our emphasis is more on the methodology and less on the application, and therefore one mainly finds in the paper general guidelines rather than analytical "recipes" on how to model securities prices. Our next research direction is "fill in the gaps" and provide practical solutions as to how to transform those guidelines in a detailed architecture of a forecasting system.

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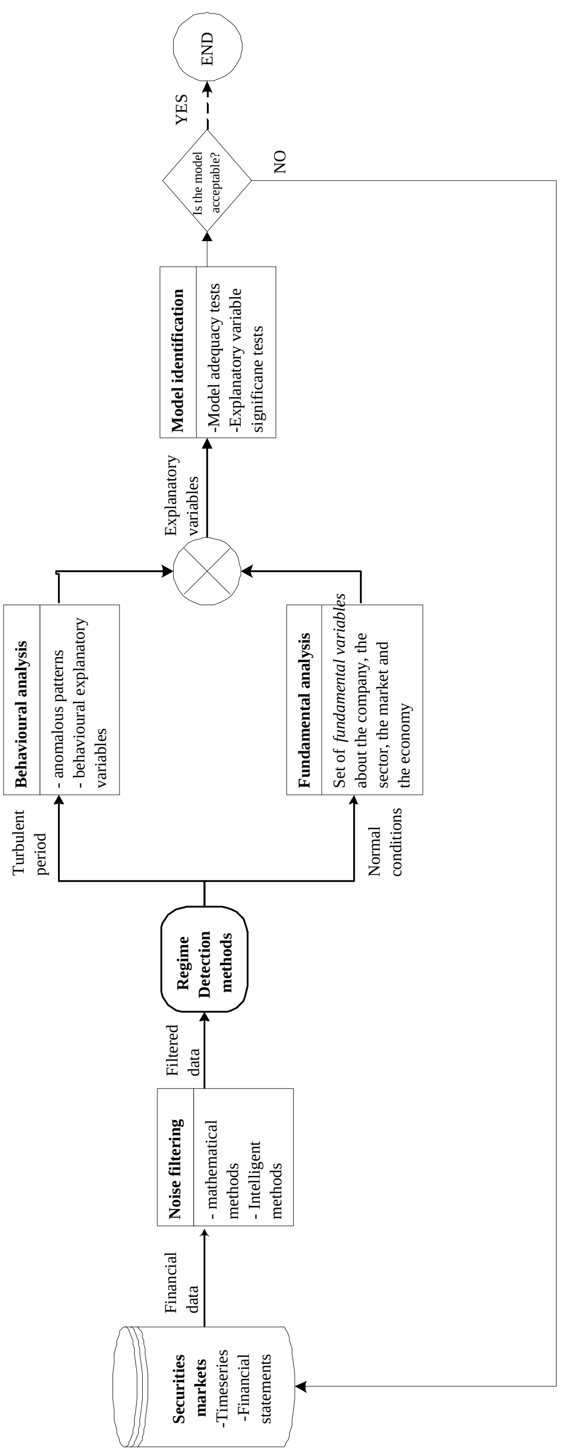

Fig. 1: A alternative framework for the modelling of securities prices.