Does Market Irrationality in the Media Affect Stock Returns?

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This paper investigates whether news suggestive of irrationality within financial markets have an impact on stock returns. We construct a lexicon of words for 'market irrationality' and score daily news articles based on the number and proportion of words they contain from the lexicon. We find that reported market irrationality has a significant negative impact on subsequent stock market returns and exacerbates stock market volatility. Furthermore, stocks with large, negative irrationality risk betas outperform stocks with large, positive betas on average by 10.3% annually. Accounting for the Fama-French factors, this results in an alpha of 8.6% annually, which is significant at the 1% level. These results suggest that a large, positive *IRR* beta amplifies a stock's reaction to market irrationality while a large, negative *IRR* beta dampens it. The subsequent *IRR* betas' mean-reversion is consistent with this conjecture.

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1. Introduction

An abundant literature has studied irrational behaviour in finance. For instance, Daniel and Titman (2000) examine how investor overconfidence can generate stock market momentum, Laibson (1997) documents empirical evidence for time-inconsistent discounting and over-valuation of the present, and Barber et al. (2006) study how noise traders can cause mispricing in the market. Shiller (2005) covers the topic in extensive detail with explorations of the effects of irrationality on housing markets, the media, and financial institutions. Yet there is no empirical evidence linking stock returns and the frequency of media characterisations of financial markets as irrational.

Our paper aims to bridge this gap and investigate what impact the use of irrational language to describe the market in news media has on stock returns. We pursue two main objectives: first, we assess the forecasting ability of a market irrationality sentiment measure extracted from the media on stock returns and volatility and, second, we examine if innovations in market irrationality represent a priced risk factor.

To do so, we construct a lexicon of words that describe irrational behaviour, then we look at the financial press and identify articles in the US over the 15-year period from 1998 to 2012 that link irrational behaviour with stock markets.[1] We begin by compiling a list of words that describe irrational behaviour and then validate it independently with three experts working in the fields of psychology and neuroscience. To construct the "market irrationality" sentiment measure, we use articles posted on the *Dow Jones Newswire*, which includes articles from a wide range of sources including the *Wall Street Journal*. To create a numerical measure, we follow Tetlock

[1]We were unable to find an existing lexicon of words describing irrational behaviour so we developed our own.

et al. (2008) and Loughran and McDonald (2011) who compute the proportion of words from a given lexicon in a given text. The irrationality sentiment measure, IRR, is formed by calculating the percentage of words from the irrationality lexicon that appear daily in a series of financial news articles.

We find that market irrationality has a significantly negative effect on subsequent stock market returns - proxied by the S&P 500 and the DJIA - and exacerbates stock market volatility, however, the full impact takes time to manifest with small downturns at first culminating in a significant negative impact after three days followed by a weak reversal almost a week later. Tetlock (2007)'s "pessimism" sentiment measure, in contrast, led to an immediate impact followed by a weak reversal a few days later. The relatively protracted impact of the market irrationality sentiment measure suggests that this information is more complex than the pessimism sentiment measure analysed by Tetlock and that it takes longer to be interpreted by investors and incorporated into stock market prices.

We next define and estimate the irrationality risk factor by normalising the market irrationality sentiment measure and calculating the residuals of an autoregressive process. We then construct portfolios using stocks drawn from the S&P 500 index - sorted on their returns' sensitivity to this risk factor. We find the distribution of irrationality risk betas to be almost symmetric about zero with some stocks having large, positive betas and some having large, negative betas. Stocks with negative irrationality betas achieve an average 5-day return of 0.35% compared to 0.15% for positive betas. This difference is highly statistically significant, amounts to about 10.3% annually, and persists throughout all our robustness checks: controlling for standard risk factors, different holding periods, subsample analysis, windsorisation, and using non-overlapping data. A possible interpretation for this surprising result is that a large, positive IRR beta amplifies the stock's reaction to market irrationality whereas a large, negative *IRR* beta causes the reaction to be dampened. Indeed, we observe that these betas mean-revert thereafter, which is consistent with a negative premium on the high-minus-low *IRR* beta portfolio. In further support of this conjecture, we find that the longer we hold the portfolios, the more significant this negative premium becomes (up to about 20 trading days). When sorting on size and book-to-market ratios, we find a concentration of the effect on raw returns occurring at the extremes i.e. small and large firms and firms with high and low book-to-market ratios.

This study contributes both to the literature on language in the media and financial markets and to the literature on investor irrationality. We show that the emphasis on irrational stock market behaviour in the media has a negative impact on the subsequent investment opportunity set. We further document that market irrationality is a priced risk factor and present an investment strategy - long on the Low IRR beta portfolio and short on the High IRR beta portfolio - that produces a significant positive return, even when accounting for standard risk factors, variations in subsamples, and outliers. Earlier literature on language has focused on measures of news sentiment (optimistic and pessimistic), measures of investor attention, etc. To our knowledge, our study is the first to examine language used in the media related to market irrationality and the first one to document a relationship between stock market prices and sources of news focussing on “market irrationality”.

The outline of this paper is as follows: Section 2 provides a brief literature review. Section 3 describes the data used in the study and details the construction of the market irrationality sentiment measure. Section 4 describes the impact of market irrationality on subsequent stock market returns and volatility. Section 5 presents the empirical results of the cross-sectional impact of irrationality risk on stock returns including robustness checks. Section 6 concludes the study.

2. Literature Review

This study relates to two different fields: media analysis and irrational behaviour in economic and financial decision-making.

Using text to provide insights into stock market movements above what can be taken from numerical data has attracted many researchers. There are several ways to approach this task: some look at external sources such as newswires or online message boards while others look at company documents such as 10-K filings or earnings reports. Some look at the volume of internet searches while others look at the words themselves. The latter splits into those that take a lexical approach and those that take a classification approach.

Antweiler and Frank (2004) and Das and Chen (2007) classify user-generated content (UGC) on internet message boards about finance into pessimistic, optimistic, and neutral signals and find that a high volume of posts about individual firms is linked to lower returns and higher volatility the following day. Tirunillai and Tellis (2012) and Da et al. (2011) use online search volume for certain firms and find that an increase in search volume for a particular company or its most popular product leads to significant positive abnormal returns. Tirunillai and Tellis (2012) also find that negative UGC leads to significant negative abnormal returns while positive UGC has no significant effect on these metrics.

The following papers all look at positive or negative sentiment using news sources. Tetlock (2007) uses a single column - *Abreast of the Market* - in the *Wall Street Journal* (*WSJ*) and a lexical approach to predict returns in the Dow Jones Industrial Average. He uses the Harvard-IV-Psychosocial dictionary, constructs sentiment factors for all its word categories, and finds that negative sentiment predicts lower stock returns on the following day and a reversal some days later. Tetlock et al. (2008)

expands the news source to include all articles in the *WSJ* and *Dow Jones Newswire* and finds similar results with the additional finding that market prices underreact to firm-specific news. García (2013) continues by looking at columns in the *New York Times* over a much longer period (1905-1958) and concludes that the result found by Tetlock (2007) is concentrated during recessions.

Loughran and McDonald (2011) also use a lexical approach but adapt the word lists used in Tetlock (2007) to be representative for financial texts.[2] Loughran and McDonald (2011) use 10-K reports and find firms whose reports contain a high proportion of negative words experience lower subsequent returns and find little effect from positive words. Li (2006) also looks at 10-K filings but specifically at words that reflect 'riskiness'. He finds that risk sentiment is associated with lower future earnings.

Da et al. (2015) and Manela and Moreira (2013) both look at investor concern and its impact on the stock market. The former use Google search volume and look for queries about household concerns such as "recession", "unemployment", and "bankruptcy". They construct a sentiment index and find that it predicts short-term return reversals, temporary increases in volatility, and mutual fund flows out of equity funds and into bond funds. Manela and Moreira (2013) also construct a sentiment index about the concerns of the average investor but use the front-page of the *WSJ* and a longer time period (1890-2009). They find that periods where people are more concerned about a rare disaster are either followed by above-average stock returns or by periods of large economic disasters. In general, they find evidence consistent with the view that rare disaster risk is an important driver of asset prices.

We next provide a brief review of the literature on irrational behaviour in economic and financial decision-making. Hirshleifer (2001) gives a detailed summary of the

[2]García (2013) also uses the Loughran and McDonald (2011) lexicon in his study.

cognitive biases that impair investors' ability to make rational decisions. He also summarises many of the ways researchers have tried to adapt their models in order to replicate this kind of behaviour. Laibson (1997) provides evidence that hyperbolic discounting may be the reason for the ongoing decline in savings rates in the U.S and Diamond and Köszegi (2003) expand on this model with a specific interest in savings and retirement.

Dow and Gorton (2006) gives an overview of the impact of noise traders on financial markets. Since they allow informed traders to capitalise on their private information, they play an essential role in modern finance theory, however, their identities, motivations, and persistence remain topics of research. Brown (1999) finds that the sentiment of individual investors is related to increased volatility in closed-end investment funds. This only happens during trading hours showing that irrational investors only affect prices through trading. Barber et al. (2006) report evidence consistent with noise trader models in which the trading of stocks by uninformed investors causes mispricing.

Tetlock et al. (2008) document an underreaction of stock markets to news, as do Huynh and Smith (2013) who find that this is the main driver of momentum effects globally.

Finally, we derive inspiration from Robert J. Shiller's book, *Irrational Exuberance* (2005). The title is a reference to Federal Reserve Board chairman Alan Greenspan who, in December 1996, is quoted as saying:

> "Clearly, sustained low inflation implies less uncertainty about the future, and lower risk premiums imply higher prices of stocks and other earning assets. We can see that in the inverse relationship exhibited by price/earnings ratios and the rate of inflation in the past. But how do we know when *irrational exuberance* has unduly escalated asset values,

> which then become subject to unexpected and prolonged contractions as they have in Japan over the past decade?"

Shiller (2005) further refers to information cascades whereby the news media make connections between current events and sequences of events in the past, which can then cause similar sequences to occur.[3]

3. Data

In this study, we use text data from the Dow Jones Newswire in order to construct the market irrationality sentiment measure. Unlike previous studies, we do not identify articles whose subject is a specific company, but focus on articles that make reference to the US stock market as a whole. This allows us to construct a market-wide irrationality sentiment measure against which we can measure individual stocks' sensitivity.

3.1. **Constructing the market irrationality sentiment measure (IRR).** The first step was to identify words that described irrational behaviour in the market. Other studies have used pre-existing lexicons, however, to our knowledge, a lexicon describing irrational behaviour did not already exist. We thus compiled an initial list of words using the Harvard-IV-4 Psychosocial Dictionary and General Inquirer categories as a template and asked three experts from the fields of neuroscience and psychology to validate which words would comprise the final lexicon.[4] The complete lexicon of words used in this study appears in Appendix I.

We performed a search of all articles on the Dow Jones Newswire, written in English, and reporting on North America, that included either of the words 'market', 'markets', 'Dow', 'NASDAQ', or 'NYSE', but not 'Moody's', "Dow Jones reported",

[3] Shiller first published his book in 2000 and in Chapter Five (pp. 85-105) he assesses the role of the news media on stock market speculation.

[4] Instructions provided to the experts and their short CVs can be found in Appendix II.

nor "Dow Jones said", within a five-word proximity of any of the words from our irrationality lexicon. To eliminate tables, summaries of news stories, articles of 50 words or fewer, as well as any weblinks, subheadings, and any attribution text that were not relevant to the news story, we applied a series of filters, the complete algorithm for which can be found in Appendix III.

We then used the LIWC 2007 program presented in Tausczik and Pennebaker (2010) to assign a score to every article equal to the percentage of words in the article that appear in the irrationality lexicon. We turned this into a daily irrationality sentiment measure (from here on referred to as *IRR*) by taking every article published after 1700 EST on day $t-1$ and before 1529 EST on day t and taking the simple average of their scores. In our sample, days $t-1$ and t refer to trading days, not calendar days. This means that most observations cover a single day's worth of news while others cover several days, usually over weekends and public holidays. This gave us daily data for the whole period from 2nd January 1998 to 31st December 2012, for which we provide the summary statistics in the first row of Table 2.

IRR includes 494 (13.1%) null observations out of a total of 3773 observations. The large number of zeros indicates that there were many days where no articles fitting our conditions were published. In total, 11727 articles fitting our conditions were available on the Dow Jones Newswire over the given period.

We continue by normalising *IRR* over the full 15-year period. We then estimate the residuals using the following autoregression with $p = 7$

$$IRR_t^{norm} = \alpha + \sum_{s=1}^{7} \phi_s \cdot IRR_{t-s}^{norm} + \epsilon_t. \tag{1}$$

$p = 7$ was chosen above other values because it represented the largest increase in the adjusted R squared (from $p = 6$ to $p = 7$) than any other value between 3 and 10. Table 1 reports the autocorrelation of the normalisation of IRR and the coefficients of the AR(7) model. It shows that IRR is weakly autocorrelated and thus is largely unpredictable.

[Insert Table 1]

We proceed by denoting the innovations estimated in (1) as $\mathcal{B}^I$. We refer to the latter variable as the **market irrationality risk factor**. Table 2 shows the summary statistics of the IRR sentiment measure along with its normalisation and the market irrationality risk factor and, due largely to the relative lack of autocorrelation in the risk factor, the statistics for the innovations do not differ greatly from those of the normalised IRR sentiment measure aside from a small negative shift. The mean and standard deviation remain roughly the same with large positive skewness and very large kurtosis denoting the appearance of several unusually large and positive values.

[Insert Tables 2 and 3]

Table 3 shows the correlation between the three Fama-French factors, the Carhart momentum factor, the raw market irrationality sentiment measure, and the market irrationality risk factor. It can be seen that the correlations between the market irrationality sentiment measure (and therefore also the market irrationality risk factor) and other standard risk factors are close to zero.

3.2. **Other data.** Stock data such as prices, returns, trading volumes, and the number of outstanding shares are collected from the Center of Research in Securities Prices (CRSP) Daily Stocks Combined File which includes all stocks actively traded on the NYSE, AMEX, and Nasdaq. Only ordinary common shares (with CRSP share code 10 or 11) are considered in this study. In addition, only companies that form part of the S&P500 index and have at least 250 days of trading data between 1st January 1998 and 31st December 2012 are included. For each company, we identify the most recent occasion on which it was included in the S&P500 index and use all its data starting from up to one calendar year prior to its inclusion. The sample includes 637 individual firms. Appendix IV presents the process in more detail. Table 4 shows the summary statistics of the daily firm sample size. Data on the Dow Jones Industrial Average was obtained from CRSP and the St. Louis Fed (FRED).

[Insert Table 4]

Data on the Fama-French factors - market excess return, size factor, book-to-market factor - as well as the implied risk-free rate and Carhart momentum factor are taken from Kenneth French's website. We also construct a *Finneg* measure using the same method for constructing the *IRR* measure but instead using the lexicon of 'negative financial' words provided by Loughran and McDonald (2011). This lexicon was constructed to correct for the fact that many lexicons of 'negative' words developed in the field of psychology include words such as *tax, cost, board, foreign, vice*, and *liability*, which, in a financial context, have a neutral meaning. The Loughran and McDonald (2011) word list specifically focuses on negative words in a financial context making it an appropriate lexicon to use for the alternative negative sentiment measure.

4. Market Activity and Irrationality

In this section, we follow Tetlock (2007) by investigating the ability of the raw market irrationality sentiment measure to forecast stock market returns and volatility. Tetlock, who considers investor pessimism, focuses on the Dow Jones Industrial Average because he derives his measure from the WSJ column 'Abreast of the Market' which covers the Dow Jones Index. Since the market irrationality sentiment measure incorporates all articles recovered from the Dow Jones Newswire, we look at the Dow Jones Industrial Average as well as the S&P 500 Index and a series of portfolios using S&P 500 firms sorted on size and book-to-market ratios.

4.1. **VARs.** We conduct a series of Vector Autoregressions (VARs) using the portfolio or stock market returns (R), the raw market irrationality sentiment measure (IRR), and a proxy for volatility using the CBOE VIX Index (VIX). We include a series of exogenous variables ($Exog$) that comprise 5 lags of share volume specific to the portfolio being analysed, dummies for the days of the week, a dummy for January, and dummies for extreme negative stock market events on the following dates: 31st August 1998 (Russian financial crisis), 14th April 2000 (dot-com bubble), 17th September 2001 (September 11th attacks), 29th September 2008, and 15th October 2008 (the subprime financial crisis).[5,6]

As in Tetlock (2007), we define the lag operator, L5, to be the transform of variable x_t to the vector consisting of the five lags of x_t, that is,

$$L5(x_t) = [x_{t-1}\, x_{t-2}\, x_{t-3}\, x_{t-4}\, x_{t-5}].$$

In this way, the first set of VARs can be expressed as

$$R_t = \alpha_1 + \beta_1 \cdot L5(R_t) + \gamma_1 \cdot L5(IRR_t) + \delta_1 \cdot L5(VIX_t) + \lambda_1 \cdot Exog_t + \epsilon_{1t} \tag{2}$$

[5]29.09.2008: The U.S. House of Representatives' failure to pass the Bush Administration's $700 billion bailout plan triggered the biggest one-day point drop in the history of the Dow Jones industrial average. This happened two weeks after Lehman's filed for bankruptcy. Source: TIME: http://content.time.com/time/specials/packages/article/0,28804,1845523_1845619_1845541,00.html. The Guardian: http://www.theguardian.com/business/2008/sep/15/lehmanbrothers.creditcrunch

[6]15.10.2008: "The Dow Jones dropped in response to a report that retail sales have reached a 3-year low and a speech by Federal Reserve Chairman Ben Bernanke in which he says the economic recovery will be slow." Source: http://www.infoplease.com/business/economy/declines-dow-jones-industrial-average.html

We focus on the γ_1s as they describe the dependence of the stock index or portfolios' returns on the market irrationality sentiment measure. Tables 5 and 6 summarise the estimates of γ_1 when R describes, respectively, stock index returns and the returns of portfolios sorted on their size or book-to-market ratios respectively.

Table 5 shows that the third lag of the irrationality sentiment measure has a significant negative impact on the Dow Jones and S&P 500 index returns at the 10% and 5% levels respectively. We can see in Table 6 that for the portfolios sorted on their size and book-to-market ratios, the irrationality sentiment measure has a significant negative impact on small firms and value firms. This is consistent with the fact that these firms are, in general, much more sensitive to adverse market conditions.[7]

Whereas in Tetlock (2007), the first lag of the 'bad news' measure is most pertinent for stock returns, the market irrationality sentiment measure is most significant at the third lag. We interpret this delayed response by recognising that irrationality is not a straight-forward concept to interpret, unlike negative or positive words as studied in other papers, so its impact may take longer to be integrated into the market. While Tetlock finds a significant impact of the "bad news" measure on the first lag and a weak reversal on the 4th lag, we show that the market irrationality sentiment measure has a longer-lasting negative impact on returns over the first week. By considering up to 10 lags instead of 5, we find a reversal around the 7th lag for both indices, however, in general, it is not statistically significant.[8]

The second set of VARs examine whether the market irrationality sentiment measure depends on stock returns. These are expressed as

[7]See Perez-Quiros and Timmermann (2000) and Guo (2004).
[8]All results on the reversals are available on request.

$$(3) \quad IRR_t = \alpha_2 + \beta_2 \cdot L5(R_t) + \gamma_2 \cdot L5(IRR_t) + \delta_2 \cdot L5(VIX_t) + \lambda_2 \cdot Exog_t + \epsilon_{2t}$$

There does not appear to be a clear causal relationship going from stock returns or volatility to the market irrationality sentiment measure as there are no significant coefficients when using either the S&P 500 index or the DJIA.[9]

The third set of VARs examines whether market irrationality affects stock market volatility. These are expressed as

$$(4) \quad VIX_t = \alpha_3 + \beta_3 \cdot L5(R_t) + \gamma_3 \cdot L5(IRR_t) + \delta_3 \cdot L5(VIX_t) + \lambda_3 \cdot Exog_t + \epsilon_{3t}$$

Table 7 shows the values for γ_3 and, once again, we find that the third lag of the market irrationality sentiment measure significantly predicts stock market volatility at the 5% level regardless of which index we use for R_t. In both cases, this means that a one standard deviation increase in the third lag of the market irrationality sentiment measure corresponds to a 0.060 point increase in stock market volatility.

4.2. **Robustness Analysis.** As a robustness check, we include a news measure to account for "bad news". We adopt the lexicon developed by Loughran and McDonald (2011) as it is designed to take into account the financial nature of the news articles we are interested in. We apply this lexicon to score the articles we collected for the market irrationality sentiment measure and call it $Finneg$ ($Finance\ Negative$).

The fourth set of VARs look at how stock returns depend on the market irrationality and negative sentiment measures. These are expressed as

(5)

$$R_t = \alpha_4 + \beta_4 \cdot L5(R_t) + \phi_4 \cdot L5(Finneg_t) + \gamma_4 \cdot L5(IRR_t) + \delta_4 \cdot L5(VIX_t) + \lambda_4 \cdot Exog_t + \epsilon_{4t}$$

[9] Coefficient estimates are available upon request.

We observe no significant results for *Finneg* when looking at either stock market index. Tetlock (2007) finds a significant negative impact on the DJIA at the first lag for his "bad news" measure with a significant reversal on the 4th lag.[10] One of the reasons we might not see this is that the two datasets are structurally different with respect to both the lexicon used to retrieve the articles and the source of the text data. Even so, after controlling for negative news, we still obtain a significantly negative coefficient for IRR on S&P 500 and DJIA returns at the third lag.

We conclude that market irrationality affects both stock returns and stock market volatility but not instantly. In general, we see a three-day lag between an increase in reported market irrationality and a decrease in stock market returns. This is especially strong for small firms and value firms. There is also an amplifying effect of market irrationality on stock market volatility concentrated on the third lag of the market irrationality sentiment measure. On the other hand, there is no clear evidence that market irrationality is predicted by either stock market returns or volatility. These results persist even after we control for bad news in the media.

5. Is Market Irrationality Priced in Stock Returns?

We have seen that market irrationality depresses the subsequent investment opportunity set. The next objective is to examine whether innovations in the irrationality sentiment measure are a common and priced source of risk in stock returns. For that purpose, we sort the sample of S&P 500 firms into ten portfolios based on their dependence on the market irrationality risk factor, $\mathcal{B}^I$. For each day in our sample and for every firm trading on that day, we run the regression

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,IRR} \mathcal{B}^I_{t-3} + \epsilon_{i,t} \tag{6}$$

[10] The values for ϕ_4 and γ_4 are available on request.

where MKT_t is the daily excess market return, $\mathcal{B}^I_{t-3}$ is the third lag of the market irrationality risk factor, and $r_{i,t}-r_{f,t}$ is the daily excess return for firm i.[11] The market irrationality factor beta, β_{IRR}, is estimated using the 25 preceding observations while controlling for the market beta, β_{MKT}. Firms whose betas are in the first decile are assigned to the first portfolio, firms whose betas are in the second decile are assigned to the second portfolio, and so on. These portfolios are held for five days and the 5-day portfolio return is calculated as the equally-weighted average of the firms in that portfolio.

In some cases, holding the portfolios for five trading days means that they are held for longer than a week; hence, we compute the 5-day Fama-French and Carhart factors by calculating the return on each factor running from trading day $t-5$ to trading day t.[12]

We find that the correlation between the third lag of the market irrationality factor and the Fama-French and Carhart factors is negligible for both the daily and 5-day estimates.[13] In addition, the $\hat{\beta}_{IRR}$s estimated by taking systematic market risk into account, using equation (6), are almost symmetric about zero. Thus, creating any portfolio that is long in both portfolio n and portfolio $11-n$: 5 and 6, 4 and 7, etc., has a market irrationality risk beta close to, albeit significantly less than, zero.[14]

5.1. **The Impact of the Market Irrationality Risk Factor on Expected Stock Returns.** Table 8 reports summary statistics of the daily returns of ten portfolios

[11]Section 4 shows that the third lag of the irrationality factor is most significant in predictability regressions of stock market returns. We perform the same analysis in (6) using the second lag of the irrationality risk factor instead and obtain similar but less significant results.

[12]When comparing these values to the weekly risk factors published on Kenneth French's website, we only find deviations when the trading week does not contain 5 trading days. This accurately reflects the difference between weekly stock returns and the 5-day stock returns we use in this paper. These results are available upon request.

[13]These data are available on request.

[14]All portfolios combining portfolio n and $(11-n)$ have negative IRR betas significant at the 5% level at least.

based on the estimated $\hat{\beta}_{IRR}$: minimum, median, maximum, mean standard deviation, skewness, and kurtosis. For the majority of these portfolios, skewness is negative suggesting that the portfolios are subject to occasional, large negative returns. This is strongest for the portfolios with large, positive market irrationality betas while the skewness of the portfolio starts to become more positive as the market irrationality beta becomes negative: the portfolio with the largest, negative market irrationality beta has very high positive skewness caused by occasional, large positive returns. This portfolio also exhibits the largest standard deviation with a large maximum and large minimum in absolute terms. All portfolios have large tails and, interestingly, many of the summary statistics are U-shaped or inverse U-shaped.

The portfolio mean returns appear to decrease almost monotonically from the Low (large, negative IRR beta) portfolio with an average 5-day return of 0.35% to the High (large, positive IRR beta) portfolio with an average 5-day return of 0.15%, less than half. This amounts to an average 5-day difference between the Low and High portfolios of 0.2% or about 10.3% annually.[15] This difference is significant at the 1% level.

We next calculate the risk-adjusted performances (alphas) for all ten portfolios sorted on the market irrationality risk factor using the performance evaluation models developed by Fama and French (1993), the three-factor model (henceforth FF), and by Carhart (1997), the four-factor model (henceforth Carhart), which are, respectively,

$$r_{i,t} - r_{f,t} = \alpha_{i1} + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \epsilon_{i,t} \tag{7}$$

and

[15] Calculated on the assumption that there are 252 trading days per year.

(8)

$$r_{i,t} - r_{f,t} = \alpha_{i2} + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,UMD} UMD_t + \epsilon_{i,t}$$

where $r_{i,t}$ is the return of portfolio i, $r_{f,t}$ is the one-day risk-free interest rate, MKT_t is the excess market return, SMB_t is the excess return of all small-cap stocks over large-cap stocks, HML_t is the excess return of value stocks over growth stocks, and UMD_t is the excess return of the prior month's winning stocks over losing stocks.

Table 9 shows the results wherein we see a strong monotonic trend running from the Low IRR beta portfolio with an alpha of 0.197% in the FF case and 0.273% in the Carhart case, to the High IRR beta portfolio with an alpha of 0.033% in the FF case and 0.059% in the Carhart case. The portfolio constructed by going long in the High IRR beta portfolio and short in the Low IRR beta portfolio produces a daily alpha of -0.164% in the FF case and -0.213% in the Carhart case. Both alphas are significant at the 1% level and suggest that a strategy that goes long in the Low IRR beta portfolio and short in the High IRR beta portfolio could deliver a significant annual alpha of about 8.6% (11.3% in the Carhart model), providing further evidence that the traditional risk factors do not fully cover the risk characteristics that drive stock returns.[16,17] We observe that the negative premium is mostly due to the large α observed for the Low IRR beta portfolio. Both High and Low IRR beta portfolios have high market betas but dissimilar betas on the HML and UMD risk factors. Note that the coefficient of the momentum factor UMD_t is negative for all market irrationality risk factor beta portfolios and larger (in absolute value) for portfolios with lower exposures to the market irrationality risk factor, implying that

[16]This strategy may, however, be less profitable once transaction costs are accounted for.

[17]This result is robust when looking at the constantly updated alpha using a rolling window of 75 observations (about 3 months). Furthermore, there are no large outliers driving this result.

the performance difference between portfolios with high and low sensitivity to the market irrationality risk factor is not driven by the returns of past-winning stocks.

The negative premium observed on the high-minus-low IRR beta portfolio seems counterintuitive at first since we would expect that high market irrationality betas are linked to higher riskiness and thus to a higher risk premium and that the converse holds for low market irrationality beta portfolios. We conjecture that a positive IRR beta amplifies a stock's reaction to market irrationality while a negative IRR beta dampens it. If this conjecture is corroborated by the data, we should observe that the IRR betas subsequently mean-revert, which should justify the negative risk premium observed on the high-minus-low IRR beta portfolio.[18]

Tables 10 and 11 test this hypothesis and display the probability that a stock in IRR beta portfolio i on day t is in IRR beta portfolio j on day $t + 5$, and on days $t + 10$, $t + 15$, $t + 20$, and $t + 25$ respectively. Already after 5 days we see that for the bottom 5 IRR beta portfolios: Low, 2, 3, 4, and 5; the probability that their component stocks have moved to a higher IRR beta portfolio is between 38 and 47%. The same is true for the top 5 IRR beta portfolios moving to a lower IRR beta portfolio. We see in Table 11 that the mean-reversion of the IRR betas increases over time and, by day $t+25$, the probability that a stock in the High (Low) IRR beta portfolio has moved to a lower (higher) IRR beta portfolio is about 86% (84%). To wit, after 25 days, it is not possible to meaningfully predict in which portfolio any given stock will be, even if you know where it is on day t.

5.1.1. *Sorting by Size, Book-to-Market Ratio, and the Market Irrationality Risk Factor Beta.* We next split the firms into 25 portfolios sorted by their size and their

[18]Analysis of the movement of stocks between different IRR beta portfolios shows that the average time any one stock stays in a given IRR beta portfolio is 2.6 days. If we do a similar analysis for stocks sorted by market capitalisation and book-to-market ratios, we find that the average time any one stock stays in a given portfolio is 23.6 and 16.8 days respectively. These results on the movement of stocks between portfolios are available on request.

estimated market irrationality risk factor betas. First, we construct a ranking of all firms according to their size; this ranking is updated every twenty-five trading days.[19] Every day, we sort all the firms into five equally-sized portfolios according to their market irrationality risk factor beta estimated on the prior 25 trading days and then use the size ranking to sort these five portfolios into a total of twenty-five equally-sized portfolios. We hold these portfolios for five days and calculate the 5-day return.

Panel A of Table 12 shows the mean 5-day returns for all Size-IRR beta portfolios and it is clear that the portfolios with negative risk betas outperform those with positive risk betas regardless of size, ranging from a difference of -0.042% for mid-size firms (not significantly different from zero) to -0.149% for large firms (significant at the 1% level). In general, we see a significant impact on small-cap and large-cap stocks but not mid-cap stocks.

We perform the same operation but use the stocks' book-to-market ratios to double-sort the portfolios rather than their sizes. Panel B of Table 12 shows the mean 5-day returns for all B/M-IRR beta portfolios and the difference between the High and Low IRR beta portfolios persists albeit without any clear monotonicity running from growth firms to value firms. For value firms, the difference between the High and Low IRR beta portfolios' returns is -0.135% (significant at the 1% level) and for growth firms, the difference is -0.102% (significant at the 5% level).

5.2. **Robustness Checks.** The results so far suggest that stocks with positive exposure to the market irrationality risk factor earn lower subsequent returns than stocks with negative exposure due to subsequent mean-reversion in their IRR betas. However, there is a possibility that this effect could have been induced by model

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[19]Size is calculated by multiplying the number of shares outstanding by the share price.

mis-specifications. We perform a series of robustness checks to help address these concerns.

5.2.1. *Holding Portfolios for Different Period Lengths.* In the main results, we hold the portfolios for five days; in Table 13 we use the same ten portfolios but instead hold them for 2, 3, 10, 15, 20, and 25 (trading) days to see if different holding periods change our results. Looking at the aggregate result, we see that increasing the length of the holding period makes the results even more significant. A holding period of 2 days gives us an average daily difference of -0.040% in favour of the Low IRR portfolio and a t-stat of -2.6760, which is already significant at the 1% level. For 3 days the t-stat increases in absolute terms to -3.3523 with an average daily difference of -0.040%. The difference becomes more significant as we consider a holding period of 20 days for which the average daily difference is -0.024% with a t-stat of -6.1297. This increasing trend in significance as the holding period lengthens is consistent with the increasing *IRR* beta mean-reversion over longer holding periods documented in Section 5.1.

5.2.2. *Subsample Analysis.* In Table 14, we examine the portfolios' performance over two separate subsamples: the first one from the 2nd March 1998 to the 1st August June 2005 and the second one from the 2nd August 2005 to the 31st December 2012. The start of the period is dictated by the time required to estimate the IRR risk betas and the mid-point is chosen such that each subsample has an equal number of observations (1867 daily observations). We see that the previous results still hold; namely, that stocks with negative IRR betas outperform stocks with positive IRR betas in both subsamples (with t-stats of -3.2770 and -2.8350 respectively, which are significant at the 1% level).

5.2.3. *Windsorisation.* To examine if our results are driven by extreme returns delivering false positives, for each firm we windsorise the data at the 1% and 2% levels (that is to say that a dataset windsorised at the $n\%$ level replaces all the observations below the nth percentile with the value at the nth percentile, and all the observations above the $(100 - n)$th percentile with the value at the $(100 - n)$th percentile). We can see from Table 15, that the results remain significant at the 5% level, even when stock returns are windsorised at the 2% level.

5.2.4. *Non-overlapping data.* The main dataset uses overlapping data, however, this runs the risk of over-emphasising extreme observations. We look at a non-overlapping dataset that reduces the number of observations from 3734 to 747 and the results are presented in Table 16. Many of the portfolios see a large increase in kurtosis and an increase in skewness highlighting the difference in the distribution of returns between portfolios with negative IRR betas and those with positive IRR betas. Despite the reduction in the number of observations, the difference between the High and Low IRR beta portfolios' returns still remains negative and significant at the 5% level.

6. Conclusion

We construct a measure of market irrationality sentiment by downloading text from the Dow Jones Newswire and calculating the proportion of words each day that describe irrational stock market behaviour. We use data from the S&P500 and DJIA indices and investigate how market irrationality influences subsequent stock market returns and volatility. We further examine whether the resulting market irrationality risk factor is priced.

Performing vector autoregressions using the Dow Jones Industrial Average, the S&P 500 index, and several portfolios constructed by sorting firms on size and book-to-market ratios, we first find evidence that an increase in market irrationality is associated with a subsequent decrease in stock market returns (as proxied by the S&P 500 and the DJIA stock indices) and more specifically among those firms that are small or have high book-to-market ratios. We find that the market irrationality sentiment measure takes more time to impact prices than other news-based sentiment measures with the most significant impact taking place 3 days after its publication. Even when taking into account share volume, volatility, and dummies for days-of-the-week, January, and five market crashes, a one standard deviation increase of the market irrationality sentiment measure is associated with, on the third day, a 4.8 basis point drop in the S&P 500 index (significant at the 5% level), a 3.4 basis point drop on the DJIA (significant at the 10% level), an 8.0 basis point drop in the portfolio of small stocks (significant at the 1% level), and a 9.1 basis point drop in the portfolio of value stocks (significant at the 1% level).[20]

We also find that a one standard deviation increase of the market irrationality sentiment measure is associated with a 0.060 increase in the VIX volatility index (significant at the 5% level) on the third day.[21] This represents 3.5% of one standard deviation of the innovations of the VIX index computed over the full 1998-2012 period. We find no evidence that stock returns, share volume, or volatility have any impact on the market irrationality sentiment measure. Our first main conclusion is that market irrationality deteriorates the subsequent investment opportunity set.

The second objective is to examine whether market irrationality is a priced risk factor and we find that the high-minus-low IRR beta portfolio generates a negative

[20]Over the full 5 trading-day period, a one standard deviation increase of the market irrationality sentiment measure is associated with a 8.9 basis point drop in the S&P 500 index (not statistically significant), a 7.3 basis point drop on the DJIA (not statistically significant), a 15.2 basis point drop in the portfolio of small stocks (significant at the 5% level), and a 19.0 basis point drop in the portfolio of value stocks (significant at the 1% level).

[21]Over the full 5 trading-day period, a one standard deviation increase of the market irrationality factor is associated with a 0.114 increase in the VIX volatility index (albeit not statistically significant).

and significant alpha after accounting for standard risk factors. We hypothesise that this counter-intuitive result is due to the fact that a high IRR beta amplifies stock returns' reactions to market irrationality while a low IRR beta dampens them. The subsequent IRR betas' mean-reversion provides a consistent explanation for the negative alpha we initially observe on the high-minus-low IRR beta portfolio.

A first extension to this paper could focus on the following question: why do stocks IRR betas subsequently mean-revert? Could this be due to uninformed investors subsequently revising their attention to the stock market irrationality exposure of individual stocks? Could it alternatively be the result of informed agents' trading patterns? Or, could it be explained by a combination of both?

Other extensions of this study could be considered. In particular, it would be interesting to investigate if market irrationality reported in the media also affects the returns of other asset classes. Moreover, it would be worthwhile to repeat the exercise by focusing on irrational words characterising stock markets that appear on the internet, financial blogs, or on social media. Finally, the pricing of market irrationality as a risk factor represents a challenge for standard asset pricing models that deserves to be further explored.

Table 1. Autocorrelation of the normalisation of *IRR* and the coefficients of the accompanying AR(7) process

	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7
IRR normalised	0.045	0.056	0.015	0.033	0.050	0.025	0.075
	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	ϕ_7
Coefficients in Equation (1)	0.038	0.048	0.005	0.026	0.042	0.015	0.068

This table reports the autocorrelation coefficients of the first seven lags of *IRR* normalised (ρ_1 to ρ_7) and the coefficients of the following autoregressive model of order seven based on a time series generated from trading days on the NYSE. The sample period is 2nd January 1998 to 31st December 2012.

Table 2. Summary statistics of *IRR*

	Min	Median	Max	Mean	Std	Skew	Kurt
IRR	0	0.308	5.755	0.445	0.509	3.556	23.704
IRR normalised	-0.874	-0.269	10.427	0	1	3.556	23.704
$\mathcal{B}^I$ (Residuals)	-1.765	-0.262	10.009	0	0.994	3.515	23.362

This table shows the minimum, median, maximum, mean, standard deviation, skewness, and kurtosis of *IRR*, its normalisation, and its innovations using the period 2nd January 1998 to 31st December 2012 inclusive (summary statistics for the innovations start on 13th January 1998).

Table 3. Correlation between key factors

	MKT	SMB	HML	UMD	IRR	$\mathcal{B}^I$
MKT	1.0000					
SMB	0.0573	1.0000				
HML	-0.1024	-0.1432	1.0000			
UMD	-0.3094	0.1005	-0.2633	1.0000		
IRR	-0.0061	0.0156	-0.0422	0.0086	1.0000	
$\mathcal{B}^I$	-0.0056	0.0198	-0.0440	0.0112	0.9935	1.0000

This table reports a correlation matrix of the following variables: market factor (MKT) defined as the excess market return; size factor (SMB) defined as the excess returns of small-cap stocks over large-cap stocks; value factor (HML) defined as the excess returns of the value stocks over growth stocks; momentum factor (UMD) defined as the excess returns of prior month winning stocks over losing stocks; IRR; and $\mathcal{B}^I$. The sample period is all trading days from 13th January 1998 to 31st December 2012 inclusive.

Table 4. Summary Statistics of daily firm sample size

	Min	Median	Max	Mean	Std	Skew	Kurt
# Firms	329	465	498	452.02	40.96	-1.47	4.18

The table reports summary statistics of daily firm sample size: minimum, median, maximum, mean, standard deviation, skewness, and kurtosis. The data period is 2nd January 1998 - 31st December 2012.

Table 5. Coefficients of *IRR* in VAR Equation (2). Values represent basis points.

	Dependent variable: R	
Irrationality	DJIA	S&P 500
IRR_{t-1}	-5.09	-4.99
IRR_{t-2}	-1.51	-2.85
IRR_{t-3}	-6.66*	-9.44**
IRR_{t-4}	-0.83	-2.80
IRR_{t-5}	-0.19	2.52
$\chi^2(5)$ $[Joint]$	5.33	7.50
p-value	0.377	0.186

The table reports the coefficients for the market irrationality sentiment measure in equation (2) when using the returns on the DJIA or S&P 500 index. It also reports the test-statistics that all coefficients are jointly 0 along with the accompanying p-values. Significance at the 10%, 5%, and 1% levels are indicated with *, **, and *** respectively.

TABLE 6. Coefficients of *IRR* in VAR Equation (2). Values represent basis points.

Panel A	Dependent variable: R					
Irrationality	Small	Size Dec. 2	Size Dec. 3	Size Dec. 8	Size Dec. 9	Large
IRR_{t-1}	-7.44	-8.17*	-7.27	-7.47*	-7.52*	-7.80*
IRR_{t-2}	-7.63	-5.48	-7.26	-4.35	-3.31	-1.61
IRR_{t-3}	-15.62***	-10.06**	-9.97**	-6.75	-6.51	-6.51
IRR_{t-4}	-2.63	-3.80	-2.48	-5.15	-5.79	-3.29
IRR_{t-5}	3.55	1.65	1.07	0.38	-1.79	0.55
$\chi^2(5)$ [*Joint*]	11.52**	9.82*	10.41*	8.91	8.78	7.60
p-value	0.042	0.081	0.064	0.113	0.118	0.180
Panel B	**Dependent variable: R**					
Irrationality	Low	B/M Dec. 2	B/M Dec. 3	B/M Dec. 8	B/M Dec. 9	High
IRR_{t-1}	-7.83*	-9.37**	-7.27*	-6.68	-6.70	-10.20
IRR_{t-2}	0.49	-4.29	-3.52	-5.22	-4.84	-9.95
IRR_{t-3}	-3.01	-4.24	-7.61*	-10.55**	-10.81**	-17.83***
IRR_{t-4}	-5.88	-2.66	-2.00	-1.24	-4.29	-6.83
IRR_{t-5}	0.07	-2.04	-1.74	3.68	5.86	7.45
$\chi^2(5)$ [*Joint*]	5.54	7.60	7.72	10.29*	10.11*	15.24***
p-value	0.354	0.179	0.172	0.067	0.072	0.009

The table reports the coefficients for the market irrationality sentiment measure in equation (2) when using the returns on portfolios whose components are ranked by their size (Panel A) and book-to-market ratios (Panel B). It also reports the test-statistics that all coefficients are jointly 0 along with the accompanying p-values. Significance at the 10%, 5%, and 1% levels are indicated with *, **, and *** respectively.

Table 7. Coefficients of *IRR* in VAR Equation (4)

R	DJIA	S&P 500
Irrationality	Dependent variable: VIX	
IRR_{t-1}	0.090*	0.086
IRR_{t-2}	0.022	0.020
IRR_{t-3}	0.119**	0.117**
IRR_{t-4}	0.004	0.005
IRR_{t-5}	-0.002	-0.004
$\chi^2(5)$ $[Joint]$	8.41	8.02
p-value	0.135	0.155

The table reports the coefficients for the market irrationality sentiment measure in equation (4) when using the returns on the DJIA or S&P 500 index. It also reports the test-statistics that all coefficients are jointly 0 along with the accompanying p-values. Significance at the 10%, 5%, and 1% levels are indicated with *, **, and *** respectively.

Table 8. Summary Statistics of 5-Day Portfolio Excess Returns sorted on $\mathcal{B}^I_{-3}$

IRR Beta	Min	Median	Max	Mean	Std	Skew	Kurt	IRR Beta
Low	-0.273	0.00336	0.355	0.00347	0.044	0.644	10.279	-0.01051
2	-0.249	0.00274	0.303	0.00214	0.033	0.012	8.993	-0.00502
3	-0.218	0.00312	0.280	0.00197	0.030	-0.039	8.977	-0.00306
4	-0.185	0.00305	0.239	0.00192	0.028	-0.100	7.951	-0.00170
5	-0.180	0.00280	0.205	0.00182	0.028	-0.244	7.545	-0.00057
6	-0.190	0.00285	0.245	0.00189	0.028	-0.209	8.862	0.00050
7	-0.184	0.00309	0.193	0.00178	0.028	-0.339	7.736	0.00163
8	-0.205	0.00301	0.194	0.00158	0.029	-0.397	7.663	0.00294
9	-0.243	0.00317	0.200	0.00215	0.031	-0.507	9.217	0.00481
High	-0.253	0.00384	0.316	0.00152	0.039	-0.547	8.815	0.01001
High - Low	-0.268	-0.00024	0.144	-0.00195***	0.028	-1.399	12.727	0.02052***
t-statistic	-	-	-	(-4.33)	-	-	-	(85.32)
High + Low	-0.526	0.00698	0.670	0.00498***	0.079	-0.006	8.800	-0.00050***
t-statistic	-	-	-	(3.87)	-	-	-	(-7.51)
High - 6	-0.191	0.00029	0.152	-0.00037	0.021	-0.679	11.321	0.00951***
t-statistic	-	-	-	(-1.08)	-	-	-	(85.12)
5 - Low	-0.264	-0.00053	0.115	-0.00165***	0.026	-1.648	15.694	0.00994***
t-statistic	-	-	-	(-3.88)	-	-	-	(78.55)

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess stock market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. Portfolios are held for five days and the 5-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. The table reports summary statistics of 5-day portfolio returns: minimum, median, maximum, mean, standard deviation, skewness, kurtosis, and average exposure to the market irrationality risk factor for the 10 decile portfolios, the portfolio going long in High and short in Low, the portfolio going long in both High and Low, the portfolio going long in High and short in 6, and the portfolio going long in 5 and short in Low. The numbers in parentheses are t-statistics.

TABLE 9. Time-Series Tests of Three- and Four-Factor Models of Equal-Weighted Portfolios sorted on $\mathcal{B}^{I}_{-3}$

IRR Beta	α (%)	MKT	SMB	HML	UMD	R^2_{adj}
Low	0.197	1.397	0.096	0.516		0.7793
	(5.78)	(111.99)	(4.01)	(23.57)		
	0.273	1.251	0.184	0.311	-0.429	0.8362
	(9.25)	(108.84)	(8.80)	(15.80)	(-36.01)	
2	0.102	1.114	-0.0175	0.392		0.8758
	(5.34)	(159.47)	(-1.30)	(32.01)		
	0.135	1.049	0.021	0.302	-0.189	0.8956
	(7.70)	(153.24)	(1.68)	(25.73)	(-26.61)	
3	0.098	1.018	-0.073	0.345		0.8850
	(5.91)	(167.36)	(-6.26)	(32.33)		
	0.114	0.987	-0.055	0.302	-0.090	0.8905
	(7.02)	(155.55)	(-4.77)	(27.75)	(-13.74)	
4	0.099	0.963	-0.098	0.352		0.8909
	(6.49)	(172.41)	(-9.06)	(35.96)		
	0.111	0.939	-0.084	0.320	-0.069	0.8945
	(7.39)	(159.96)	(-7.84)	(31.74)	(-11.34)	
5	0.090	0.935	-0.090	0.350		0.8813
	(5.80)	(164.26)	(-8.16)	(35.04)		
	0.100	0.917	-0.079	0.325	-0.053	0.8835
	(6.44)	(152.08)	(-7.20)	(31.42)	(-8.45)	
6	0.099	0.939	-0.074	0.319		0.8855
	(6.44)	(167.84)	(-6.89)	(32.46)		
	0.108	0.921	-0.064	0.294	-0.052	0.8877
	(7.10)	(155.45)	(-5.92)	(28.90)	(-8.55)	
7	0.089	0.940	-0.072	0.300		0.8827
	(5.73)	(165.73)	(-6.61)	(30.15)		
	0.098	0.923	-0.062	0.276	-0.051	0.8847
	(6.34)	(153.46)	(-5.68)	(26.77)	(-8.12)	
8	0.064	0.976	-0.036	0.297		0.8802
	(3.92)	(163.37)	(-3.10)	(28.29)		
	0.075	0.956	-0.023	0.267	-0.064	0.8831
	(4.65)	(151.26)	(-1.99)	(24.60)	(-9.75)	
9	0.114	1.067	0.008	0.253		0.8832
	(6.49)	(165.46)	(0.66)	(22.35)		
	0.122	1.052	0.017	0.233	-0.042	0.8842
	(6.92)	(153.36)	(1.34)	(19.80)	(-5.85)	
High	0.033	1.266	0.165	0.159		0.8349
	(1.29)	(133.47)	(9.02)	(9.56)		
	0.059	1.216	0.195	0.089	-0.147	0.8435
	(2.34)	(123.13)	(10.87)	(5.26)	(-14.34)	
High-Low	-0.164	-0.131	0.069	-0.357		0.0560
	(-3.73)	(-8.18)	(2.22)	(-12.68)		
	-0.213	-0.035	0.011	-0.222	0.282	0.1195
	(-5.02)	(-2.11)	(0.38)	(-7.82)	(16.43)	

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. Portfolios are held for five days and the 5-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. The table reports the evaluation results of the three- and four-factor models. The numbers in parentheses are t-statistics.

Table 10. Probability of a stock in portfolio i comprising part of portfolio j 5 trading days later

IRR Beta	$t+5$										Total probability of
t	Low	2	3	4	5	6	7	8	9	High	increase/decrease †
Low	0.617	0.189	0.070	0.038	0.024	0.018	0.013	0.011	0.010	0.010	0.383
2	0.190	0.347	0.198	0.100	0.058	0.038	0.026	0.019	0.015	0.011	0.463
3	0.070	0.198	0.265	0.187	0.109	0.068	0.043	0.028	0.020	0.012	0.467
4	0.037	0.101	0.186	0.230	0.178	0.111	0.069	0.044	0.028	0.015	0.446
5	0.024	0.058	0.109	0.179	0.218	0.177	0.110	0.068	0.040	0.018	0.413
6	0.017	0.038	0.066	0.113	0.174	0.222	0.176	0.109	0.060	0.026	0.408
7	0.013	0.026	0.043	0.070	0.112	0.179	0.232	0.186	0.100	0.039	0.443
8	0.011	0.019	0.030	0.043	0.066	0.110	0.188	0.263	0.199	0.071	0.467
9	0.010	0.013	0.019	0.027	0.038	0.060	0.102	0.202	0.343	0.185	0.472
High	0.011	0.012	0.012	0.015	0.019	0.026	0.038	0.071	0.184	0.613	0.387

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. This table reports the number of times in the dataset any stock in portfolio i was in portfolio j 5 trading days later as a fraction of the total number of stocks in portfolio i summing over all observable days. † The highlighted value in column 'Total probability of increase/decrease' refers to an increase in IRR beta for portfolios Low, 2, 3, 4, and 5, a decrease in IRR beta for portfolios 6, 7, 8, 9, and High, and is the sum of all highlighted values in that row.

Table 11. Total probability of a stock in portfolios Low, 2, 3, 4, and 5 (6, 7, 8, 9, and High) appearing in a higher (lower) IRR beta portfolio later

	Number of days after stocks appeared in portfolio i			
IRR Beta (Portfolio i)	10	15	20	25
	(Probability of being in a higher IRR beta portfolio)			
Low	0.548	0.668	0.762	0.838
2	0.588	0.668	0.729	0.780
3	0.560	0.619	0.665	0.705
4	0.510	0.549	0.582	0.610
5	0.458	0.481	0.495	0.505
	(Probability of being in a lower IRR beta portfolio)			
6	0.452	0.471	0.481	0.491
7	0.511	0.548	0.579	0.604
8	0.558	0.619	0.666	0.705
9	0.597	0.676	0.739	0.791
High	0.560	0.682	0.779	0.856

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. This table reports the number of times in the dataset any stock in portfolio i was in a higher or lower (as indicated) IRR beta portfolio a specified number of trading days later as a fraction of the total number of stocks in portfolio i summing over all observable days.

Table 12. Mean 5-Day Portfolio Excess Returns in % sorted by Size and IRR

Panel A	Size				
IRR Beta	Small	2	3	4	Large
Low	0.505	0.341	0.174	0.134	0.162
2	0.340	0.209	0.198	0.121	0.096
3	0.340	0.206	0.206	0.133	0.076
4	0.359	0.217	0.133	0.148	0.071
High	0.379	0.295	0.132	0.089	0.012
High-Low	-0.126***	-0.046	-0.042	-0.045	-0.149***
t-statistic	(-2.6156)	(-1.0924)	(-1.0659)	(-1.0568)	(-3.9128)

Panel B	Book-to-Market Ratio				
IRR Beta	Low	2	3	4	High
Low	0.279	0.261	0.199	0.243	0.353
2	0.141	0.154	0.161	0.204	0.332
3	0.146	0.159	0.178	0.184	0.283
4	0.157	0.129	0.183	0.164	0.273
High	0.177	0.141	0.131	0.254	0.218
High-Low	-0.102**	-0.120***	-0.068*	0.012	-0.135***
t-statistic	(-2.4175)	(-3.0077)	(-1.9207)	(0.3307)	(-2.6669)

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into five portfolios based on the sensitivities of their excess returns to three-period-lagged innovations in the normalised *IRR*. Stocks are chosen as companies that are part of the S&P500 index are will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. In each sensitivity quintile, stocks are assigned into five further portfolios based on their market capitalisations (Panel A) or their book-to-market ratios (Panel B), updated every 25 trading days over the sample period. Portfolios are held for five days and the 5-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. This table reports mean 5-day portfolio returns. The numbers in parentheses are t-statistics.

Table 13. Mean Holding Period Portfolio Returns in % for different holding periods sorted on $\mathcal{B}^I_{-3}$

	Holding Period (days)					
IRR Beta	2	3	10	15	20	25
Low	0.149	0.216	0.626	0.913	1.200	1.452
2	0.091	0.135	0.404	0.592	0.790	0.973
3	0.090	0.126	0.394	0.557	0.725	0.885
4	0.075	0.113	0.393	0.554	0.710	0.874
5	0.066	0.104	0.349	0.517	0.685	0.837
6	0.077	0.107	0.391	0.585	0.754	0.905
7	0.067	0.107	0.382	0.568	0.743	0.907
8	0.053	0.087	0.327	0.523	0.703	0.910
9	0.088	0.135	0.394	0.574	0.762	0.965
High	0.068	0.096	0.311	0.507	0.716	0.944
High-Low	-0.080***	-0.120***	-0.315***	-0.405***	-0.484***	-0.508***
t-statistic	(-2.6760)	(-3.3523)	(-5.1340)	(-5.7475)	(-6.1297)	(-5.8182)

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. Portfolios are held for a set number of days and the multi-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. The table reports mean portfolio returns. The numbers in parentheses are t-statistics.

Table 14. Subsample Analysis - Portfolios sorted on $\mathcal{B}^{I}_{-3}$

	2nd March 1998 - 1st August 2005	2nd August 2005 - 31st December 2012
IRR Beta	Mean (%)	Mean (%)
Low	0.414	0.279
2	0.202	0.226
3	0.205	0.189
4	0.203	0.182
5	0.227	0.137
6	0.202	0.176
7	0.210	0.146
8	0.209	0.108
9	0.279	0.151
High	0.200	0.103
High-Low	-0.214***	-0.176***
t-statistic	(-3.2770)	(-2.8350)

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. Portfolios are held for five days and the 5-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. This table reports mean 5-day portfolio returns. The numbers in parentheses are t-statistics.

Table 15. Windsorised - Portfolios sorted on $\mathcal{B}^{I}_{-3}$

	1%	2%
IRR Beta	Mean (%)	Mean (%)
Low	0.255	0.235
2	0.209	0.195
3	0.191	0.180
4	0.193	0.180
5	0.185	0.187
6	0.171	0.156
7	0.184	0.168
8	0.172	0.173
9	0.202	0.200
High	0.165	0.156
High-Low	-0.091**	-0.079**
t-statistic	(-2.3760)	(-2.2429)

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. Portfolios are held for five days and the 5-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. This table reports mean 5-day portfolio returns. The numbers in parentheses are t-statistics.

Table 16. Summary Statistics of 5-Day Portfolio Excess Returns sorted on $\mathcal{B}^I_{-3}$ with non-overlapping data

IRR Beta	Min	Median	Max	Mean	Std	Skew	Kurt
Low	-0.273	0.00354	0.355	0.00349	0.046	0.382	12.449
2	-0.249	0.00263	0.303	0.00220	0.035	0.187	15.766
3	-0.218	0.00292	0.280	0.00189	0.032	0.303	15.679
4	-0.185	0.00379	0.239	0.00239	0.029	0.078	12.508
5	-0.180	0.00338	0.205	0.00185	0.029	-0.260	10.092
6	-0.190	0.00300	0.245	0.00182	0.029	0.107	14.434
7	-0.184	0.00347	0.167	0.00171	0.028	-0.396	8.659
8	-0.205	0.00369	0.194	0.00162	0.030	-0.474	10.509
9	-0.225	0.00383	0.200	0.00229	0.032	-0.590	10.648
High	-0.253	0.00458	0.316	0.00147	0.040	-0.377	12.877
High - Low	-0.159	-0.00046	0.106	-0.00202**	0.026	-1.039	9.110
t-statistic	-	-	-	(-2.10)	-	-	-

Every day from the 16th January 1998 to the 31st December 2012, using prior 25 trading days of observations, we regress excess stock returns on the excess market returns and three-period-lagged innovations in the normalised *IRR*, and stocks are assigned into ten portfolios based on the sensitivities of their excess returns to these innovations. Stocks are chosen as companies that are part of the S&P500 index or will be within one year, and that are trading Ordinary Common Shares for which CRSP has data. Stocks that appear in the S&P500 multiple times over the sample period are only included for their most recent appearance. Portfolios are held for five days and the 5-day portfolio return is calculated as the equal-weighted average of the returns of all stocks in the portfolio. The table reports summary statistics of 5-day portfolio returns: minimum, median, maximum, mean, standard deviation, skewness, and kurtosis. The number in parentheses is the t-statistic. Non-overlapping data reduces the number of observations from 3734 to 747.

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Appendix I: The Irrationality Lexicon

Words marked with an asterisk (*) were not used to select the news articles in the first part of constructing the market irrationality sentiment measure but were later included when scoring the articles.

ABERRANT
ABSURD
ABSURDITY
ACCURSED
ALARMING
ANARCHIC
ANARCHY
ANXIOUS
BAFFLE
BAFFLED
BAFFLING
BARBAROUS
BELLIGERENT
BERSERK
BIZARRE
BONKERS
BRAINLESS
BUBBLE*
BUBBLES*
BURST*
CALAMITY
CAPRICIOUS
CHAOS
CHAOTIC
CHILDISH
COMMOTION
CONFOUND*
CONFOUNDED
CONFOUNDING
CONFUSE*
CONFUSED
CONFUSION
CONTRADICTORY
CRASH*
CRASHED*
CRASHES*
CRASHING*
CRAZE
CRAZED
CRAZINESS
CRAZY
DAFT
DELIRIOUS
DELIRIUM
DELUSION
DELUSIONAL
DEMENTED
DEMENTIA
DEPRAVED
DERANGED
DESPAIR
DESPAIRED*
DESPAIRING
DISORDER
DISORDERED
DISORGANISE
DISORGANISED*
DISORGANIZE*
DISORGANIZED*
DISTRUST
DISTRUSTFUL
DISTRUSTING*
DIZZY

ECCENTRIC
ECCENTRICITY
ENVIOUS
ERRATIC
FANATIC
FANATICAL
FOOLISH
FOOLISHNESS
FRANTIC
FRANTICALLY
FRAUGHT
HAVOC
HYPOCRISY
HYPOCRITE
HYPOCRITICAL
HYSTERIA
HYSTERIC
HYSTERICAL
IDIOCY*
IDIOT
IDIOTIC
IGNORANCE
IGNORANT
ILLOGICAL
IMPATIENT
INCOHERENCY*
INCOHERENT
INCONCEIVABLE
INCONSISTENCY
INCONSISTENT
INSANE
INSANITY
INSTABILITY
IRRATIONAL
IRRATIONALITY
IRRESPONSIBLE
JITTERY
LUDICROUS
LUNACY
LUNATIC
MAD
MADMAN
MADNESS
MANIA*
MANIC*
MOODY
NEEDLESS
NEUROTIC
NONSENSE
NONSENSICAL
OBSTINATE
PANIC
PANICKING*
PARANOIA
PARANOID
PERPLEX
PERPLEXED
PERPLEXING
PERVERSE
PREPOSTEROUS
PSYCHO
PSYCHOTIC
REASONLESS
STUPID
STUPIDITY
SUPERSTITION
SUPERSTITIOUS
UNHINGED
UNREASONABLE
UNREASONABLY*
UNRELIABILITY
UNRELIABLY*
UNSETTLE*
UNSETTLING
UNSOUND
UNSTABLE
UNWISE
UNUSUAL

Appendix II: The Experts

Prior to our study, a lexicon consisting of words directly relating to the concept of irrationality was not readily available, despite diligent searching. In response to this, we worked to construct our own lexicon, starting by looking through the entire Harvard IV Psychosocial Dictionary for relevant words and compiling them into a single list. We then gathered a team of experts from the fields of neuroscience and psychology, gave them the word list, and the following set of instructions.

"We are looking at the use of language in connection with the way financial journalists describe stock markets and the people who trade on the stock market

You MUST complete this task independently from each other and with as little influence from others as possible. We recommend you go through the list on your own at least twice if you have the time.

1. Study the list of words IRRATIONALITY LEXICON.txt.

    - If you think a word should appear in the IRRATIONAL category, indicate this with a '1' following the word.
    - If you think a word should appear in the IRRATIONAL category but only when preceded by the word TOO, indicate this with a '1T' following the word.
    - If you think a word should appear in the IRRATIONAL category but only when preceded by the word NOT, indicate this with a '1N' following the word.

    - If you think a word should appear in the EXCESSIVE category, indicate this with a '2' following the word.
    - If you think a word should appear in the EXCESSIVE category but only when preceded by the word TOO, indicate this with a '2T' following the word.

- If you think a word should appear in the EXCESSIVE category but only when preceded by the word NOT, indicate this with a '2N' following the word.

- If you think a word should appear in the INSUFFICIENT category, indicate this with a '3' following the word.
- If you think a word should appear in the INSUFFICIENT category but only when preceded by the word TOO, indicate this with a '3T' following the word.
- If you think a word should appear in the INSUFFICIENT category but only when preceded by the word NOT, indicate this with a '3N' following the word.

If you think a word should be rejected entirely, indicate this with a '0' following the word.

If a word fits into more than one of these categories, please list all of the appropriate categories with the most pertinent first.

If you think a word should appear in a related category other than the above, use successive numbers ('4', '5', '6', etc.) and a key explaining what category these numbers pertain to.

If the word fits into a custom category but only when preceded by the word TOO, append the number with the letter 'T'.

If the word fits into a custom category but only when preceded by the word NOT, append the number with the letter 'N'.

Notes.

Please rate words based on their most common usage. If a word could be considered IRRATIONAL in one context but is more likely to occur in a context where this is not the case, please do not include it in the IRRATIONAL category.

Categories.

IRRATIONAL. Words that strongly imply that the subject is acting irrationally.

EXCESSIVE. Words that strongly imply that the actions the subject is taking are inappropriate in the sense that they go too far (overaction or overreaction).

INSUFFICIENT. Words that strongly imply that the actions the subject is taking are inappropriate in the sense that they don't go far enough (insubstantial action or reaction).

2. When we've received the reports from all three judges, we will put all words into the categories that at least 2 out of 3 judges have put them in.

New words that were included by a single judge will be put into a separate list alongside the number corresponding to its suggested category.

New words that were included by more than one judge and put into a category that both judges agree on, will be placed into that category without further investigation.

New categories will be supplied as separate lists and will contain any words that a judge felt belonged in that category that were not put into an existing category by both of the other judges.

New categories will also be assigned their own number e.g. '4'.

Words that were not assigned in the first phase or were introduced in the first phase, either by a single judge or by multiple judges with conflicting categorisations, will be provided in a new list.

This list should then be studied and processed in the same way the first one was, except now with the new categories in mind."

After the round 1 lexicons had been submitted, we made some additional rules on the definition of agreement in order to prevent too many words from being unassigned. If 2 experts agreed on a category but one added the preceding word "Too" and the other one didn't, we counted that as an agreement and included the word in that category WITH the preceding word "Too".

If one expert included a word with "Too" in the Excessive (Insufficient) category and another expert included the same word with "Not" in the Insufficient (Excessive) category, and the third expert did not contradict this (by suggesting the word fit into no category for example), we counted this as an agreement and included the word in both categories with the suggested preceding words.

Note: We did not use the EXCESSIVE or INSUFFICIENT lexicons in the final study, nor did we use any of the words with the preceding "too" or "not", thus those words are not included in Appendix I to prevent confusion.

We chose our experts on the basis of their backgrounds. Here is a brief outline of their backgrounds.

Expert 1				
PhD	Neuroscience	University of Geneva	2012	Ongoing at time of research
Master's	Neuroscience	University of Geneva	2011	2012
Bachelor's Specialism: Major: Minor:	Biology Behaviour, Genetics, and Neurobiology Biology Psychology	University of Toronto	2007	2010
Key Skills	fMRI Data Anlysis Behavioural Studies DTI Analysis			
Expert 2				
PhD	Neuroscience	University of Geneva	2009	Ongoing at time of research
Bachelor's (Honors) (Cum laude)	Biology	Yale University Clinical Advancement Lab	2005	2009
Research Experience	Psychology	Carnegie Mellon University	2002	2005
Selected Publications		Clinical Neuropsychology	2012	
		International Journal of Psychology	2011	
		Journal of Experimental Social Psychology	2010	
Expert 3				
PhD	Psychology	Goldsmith's, University of London	2006	2010
Master's	Neuroscience	Louis Pasteur University	2001	2003
Bachelor's	Physics	Imperial College	1997	2000
Selected Publications		NeuroImage	2013	
		European Journal of Neuroscience	2010	
		BMC Neuroscience	2009	

Appendix III: The Articles

The articles were chosen by searching the Factiva database from the 1st January 1980 to the 31st May 2013 for any articles that contained any of the words from the Irrationality lexicon within a five word radius of any of the words "Market", "Markets", "Dow", "NASDAQ", or "NYSE" and did not include the phrases "Moody's", "Dow Jones reported", or "Dow Jones said". "Moody's" is excluded because "moody" is contained in the Irrationality lexicon. Articles are limited to those written in English and relating to the North American continent and were sourced from the entire range of Dow Jones newswires.

The articles are categorised based on several rules.

- Any articles whose headlines contain either "Highlights" or "Summary" are categorised as summaries. In general, these articles are compliations of news stories that cover a broad range of news items. More often than not, the specific news item we are interested in is published separately and appears in multiple summaries over a 24-hour period receiving perhaps 3 or 4 extra matches than we would expect from a standard news article. We keep these articles for robustness checks.
- Similarly, any article that has strictly more than 10% of its lines beginning with a numeral is categorised as a summary. This is because these articles normally consist of a time-stamped rundown of events over an extended period of time.
- Any articles whose headlines contain "RealTick" are excluded. These articles only ever come in the form of tables and we have no interest in those.
- Any articles containing fewer than 50 words are excluded because these are usually just headlines with no body.

- Any line within an article that contains 3 or more consecutive spaces followed by any text is excluded. This has the effect of removing most of the tables embedded in an article without losing any of the major information; it also removes some subheadings, some cases of the authors' names in the texts, and links to other articles that have no relation to the article in question due to their tendency to be indented. Any article that has 50% or more of its lines categorised in this way is excluded entirely.
- Any line within an article that contains the string "http" is excluded as this very rarely refers to anything other than an advert for the site that published the article.
- Articles are ranked in importance according to their time-stamps. Articles released between 00:00 ET and 15:29 ET are given primary importance because this gives all agents enough time to react to the news and have an effect on the market. Articles released between 15:30 ET and 16:59 ET are given tertiary importance because the number of agents that will react to this news is limited and so the signal is likely to be confused. Articles released between 17:00 ET and 23:59 ET are given secondary importance because they are too late for anyone to make use of on the day they are published but may have an effect on the market on the following day.

Appendix IV: Company Selection

Start with 720 unique CUSIPs.

- 3 companies have overlapping inclusions in the index based on PERMCO. This leaves us with 717 unique companies.
- We submit these CUSIPS to CRSP and retrieve their returns data. 687 unique companies remain.

- We keep only observations whose trading status is active, whose share code is 10 or 11, and whose exchange code identifies the NYSE, AMEX, or NASDAQ. 656 unique companies remain.
- We remove any observations that occurred prior to 365 calendar days before a company's entry into the index and any observations following its exit, any observations with no return data, and any observations belonging to a company with fewer than 250 observations following these changes. This leaves us with a final total of 637 unique companies.