# Narrative Economics and Market Bubbles

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**Abstract**

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*Keywords: economic narratives; investor emotions; internet bubble; Global Financial Crisis; market pricing*

JEL Codes: A12, B41, G01, G12, G41

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## Abstract

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## 1. Introduction

Shiller (2019) argues that economists need to explore the role of popular narratives in trying to explain major economic events. Such narratives consist of often conflicting stories (including songs, jokes, theories, explanations, and plans) about salient events which people talk about and repeat, and employ in meeting the human need to make sense of what is going on. These stories are contagious and emotionally charged, which gives them their power, and dynamic: they change over time.

The part played by the emotions of economic agents, and social and group processes, in extreme economic events such as market bubbles, needs to be properly recognized. At the heart of Shiller's (2014) definition of bubbles are "the emotions of investors, and the nature of news and news media" (p. 1487), the latter being a key generator and disseminator of economic narratives. Their power resides in the emotions they provoke in market participants, which drive their decisions. Importantly, it often does not matter whether such narratives have a factual basis or not, and whether they are coherent, for them to be believed and disseminated – wishful thinking often plays an important role in their spread. We act on such stories often without reflection or thought but emotionally.

To illustrate the powerful economic impact narratives can possess, Shiller (2017) explores the economic history of the 1920-1921 Depression, the Great Depression of the 1930s and the Great Recession of 2007-2009 in terms of the respective popular narratives of the times. For each of these major economic crises he provides a wide range of superficially plausible (as long as one doesn't look too deeply) stories or explanatory narratives, both conventional and less-conventional, the most salient ones seemingly having high degrees of emotional resonance.[1] In his book *Narrative Economics*, Shiller (2019) takes a broader perspective, and examines nine perennial narrative themes that influence important economic events including stock market bubbles (chapter 16) which we also consider empirically in this paper.

Narratives about what actually happens during major market events such as financial crises and asset pricing bubbles (e.g., Mackay, 1852; Galbraith, 1993; Cassidy, 2002; Tuckett and Taffler

[1] For example, Shiller (2017) lists the following illustrative narratives for the Great Depression: the stock market drop on October 28, 1929, moralizing about the excesses of the "Roaring Twenties", a repeat of 1920-1921, the shopping behavior of housewives, the rising leftist or Communist movement and associated conspiracy theories, the frightening narratives coming out of Europe and Asia including the Japanese occupation of Manchuria, the genocide of ethnic Ukrainians by Stalin, the rise of Hitler, and stories about business people committing suicide.

2008; Aliber and Kindleberger, 2015; Shiller, 2019; Taffler et al. 2020) are first and foremost descriptions of highly emotional speculative processes. Terms such as excited, euphoric, exuberant, manic, depressed, anxious, blame, illusion, delusion and panic etc., abound. In this paper we seek to explore how the nexus of contemporaneous popular stories driving investor emotions is associated with the economic behavior of market participants as reflected in market movements during asset pricing bubbles and financial crises. To do this we explore how the financial media reports on, and seeks to explain, extreme market events.

Rather than seeking to privilege particular narratives as the most likely causes of economic events, Shiller (2017) views economic behavior as being driven by their confluence in the form of "epidemics of narrative". Despite their often-conflicting nature, the common factor in all of these stories is their emotive power. Shiller (2019) acknowledges it is difficult to distinguish correlation and causality in the relationship between popular economic narratives, and economic behavior. In addition, such stories often conflict; how can we actually "sort through them" (p. 286) and make sense of what is really going on? One approach to do this, he suggests, is to use multiple appropriately trained research assistants to track such narratives, and "to classify and quantify them according to their *essential emotional driving f*orce" (p. 287, emphasis added).

In this paper, we follow Shiller in viewing emotionally-charged narratives as key determinants of economic behavior and crises, and suggest a less resource-intensive approach to measuring the association between constellations of economic narratives and the actions of economic agents. Specifically, employing textual analysis approaches, we focus on the emotions such narratives generate, and their empirical association with the trading decisions of investors.[2]

Figure 1 provides a schematic representation of the relationships we measure, explicitly recognizing their joint determination, and interrelated nature of the underlying processes. The figure illustrates how such things as events, speculations, and rumors etc. are used in the construction of economic narratives. These generate the powerful emotions which drive investor decisions, and consequently, market prices and volatility. However, market behavior will also be reflected in stories written about the market in the media,and will likewise impact investor

[2] In this paper we focus on the key role 'integral' or fundamental emotions such as excitement, anxiety, denial and guilt play in investment decisions rather than 'incidental' emotions such as mood and sentiment (e.g., Hirshleifer and Shumway, 2003; Edmans, Garcia and Norli, 2007; Hirshleifer, Jiang and DiGiovanni, 2020) which have a more general and short lived effect on decision making.

emotions. Similarly, salient investor emotional states will influence financial journalists, and other commentators, and analysts.[3]

**<<<Figure 1 here>>>**

We examine two recent extreme market events: the internet, ‘new economy’ or ‘dot.com’ bubble of 1998-2002, and the Global Financial Crisis (GFC) of 2007-2011. However, while the former bubble was an equity market bubble largely restricted to internet stocks, the Global Financial Crisis was driven by the collapse in real estate prices, and had a much more severe and wide-spread impact. The bursting of the internet bubble was not immediately associated with a fall in output. Although GDP shrank in the first and third quarters of 2001, and the US economy was classified by the NBER as in recession for eight months from March to November 2001, the actual contraction was short lived. In contrast, the GFC was characterized by a sharp fall in GDP and collapse in the S&P 500, followed by only a slow recovery in both economic output and stock market prices.

This paper investigates, in particular, the relationship between the emotions economic narratives generate, and market returns and market uncertainty, both during the course of the two major market crises we explore, and non-crisis control periods. We do this by analyzing a large corpus of relevant articles published in the financial media employing rich context-specific keyword dictionaries constructed to measure a range of investor emotions (excitement, anxiety, mania, panic, revulsion/blame, denial, and guilt). We seek to understand how economic narratives are associated with investor behavior via the agency of the emotions they engender.

The interrelationships shown in Figure 1, in practice, make it very difficult to disentangle causality, as Shiller (2019) emphasizes.[4] In any case, emotions and market movements are frequently synchronous. In his seminal book *Thinking, Fast and Slow* (2011), the cognitive psychologist Daniel Kahneman draws on extensive psychological research to describe two broad types of mental activity. System 1 is intuitive or reflexive, and System 2 is reflective and

[3] These latter are likely to be equally caught up emotionally by the same contagious stories and dramatic market movements which will be reflected in what they write, again reinforcing the different feedback loops in Figure 1.

[4] This is also manifest in experimental bubble markets. For example in their interesting study measuring emotional state using face reading software, Breaban and Noussair (2018) work with lags of seconds. Also see Andrade, Odean, and Lin (2016).

reasoning.[5] The former is characterized by being automatic, effortless and emotional, whereas the latter is slow, controlled and effortful. System 1 generates impressions which are easy and quick to act on, System 2 is involved with judgments which are explicit and deliberate. Emotions are processed almost instantaneously, but analysis, thought and reflection take longer before being translated into action. Therefore, we would expect the emotional impact of powerful economic narratives to be reflected very quickly in market prices, whereas 'rational' System 2 processes may only be reflected with a lag. As such, this paper specifically focuses on the contemporaneous role played by narrative economics in explaining market behavior. We argue such understanding is important in its own right.

Our empirical analysis supports the direct link between the emotional impact of economic narratives, and the investment behavior of economic actors. We show how both during the new economy bubble, and the Global Financial Crisis, investors were driven by deep-seated emotions as manifest in the market narratives current at the time. Specifically, we demonstrate how popular stories explain a significant proportion of market activity in these two extreme periods through the agency of the emotions they generate. This is of the order of 40% in the case of market returns, and between 30% and 70% for market uncertainty depending on how it is measured. First, as the bubbles inflated, investors became caught up in the excitement in a powerful way, with anxiety repressed in the departure from underlying reality.[6] However, when the bubbles burst, emotions went into reverse, investors panicked, with internet stocks, and in the latter case stocks generally, now reviled and dumped as quickly as possible.

We find market returns are positively correlated with 'exciting' investor emotions of excitement and mania, and negatively with 'frightening' emotions (anxiety, panic, revulsion/blame, denial and guilt). Not surprisingly, these emotions are much more powerful in our two bubble periods than in non-bubble periods. In parallel, we show how our exciting emotions dominate in the up phase of a bubble, and our frightening emotions when it collapses. We also explore how market uncertainty, as proxied by market volatility, trading volume,[7] and the Baker, Bloom, and Davis (2016) news-

[5] Kahneman (2003), which is a revised version of his Nobel Prize address, discusses these issues directly in the context of behavioral economics.

[6] The first sentence of Shiller's (2019) Chapter 16 Stock Market bubbles points this out directly: "Narratives about stock market bubbles are stories about excitement and risk taking …".

[7] We scale dollar trading volume by total market capitalization to control for the impact of price increases or decreases.

based economic policy uncertainty (EPU) index, is dealt with emotionally. Our empirical results clearly demonstrate how increased levels of uncertainty lead to anxiety, panic and associated emotions in the minds of investors, which affect their trading behavior. Our main conclusion is that the emotions economic narratives generate are important in helping to explain market behavior, and it is possible to measure these empirically. We also show that our emotion keyword dictionaries are robust across different market crises and time periods.

We contribute to the literature in several ways. First, we build on Shiller's insights into the role narratives play in explaining economic events by measuring empirically the different emotions these reflect, and their relationship with market dynamics during asset pricing bubbles. Second, our real world findings contribute to the debate about the ecological validity of experimental asset markets. In recent papers in this journal, Andrade et al. (2016) and Breaban and Noussair (2018) create simulated markets that generate price bubbles and crashes and explore the relationship between participants' emotions and investment decisions. Both laboratory studies suggest that students' emotional states and market dynamics are correlated in a similar way to how market pricing bubbles are highly emotional events for investors in real world markets. Finally, we extend tone-based sentiment analysis methodology widely used in finance (e.g., Henry and Leone, 2016; Loughran and Mcdonald, 2016), and show how to it is possible to extract rich emotional data from financial media. In particular, we develop seven distinct emotion keyword dictionaries to measure fundamental emotions that reflect market behavior. These dictionaries have the potential for wider application. This paper proceeds as follows. In the next section we present our underlying theory and motivation, and establish our main propositions. Section III then describes our content analysis emotion keyword dictionary building process, our data research corpus and research method. Empirical tests of our main thesis follow in results section IV. Our final section V discusses and concludes.

## 2. Theory and Motivation

### *2.1 Economic Narratives, Storytelling, and Market Behavior*

Storytelling is a fundamental process by which we make sense of the world around us. As a species, human beings can be described as "homo narrans" (Fisher, 1984, p. 6) or "homo fabulans – the tellers and interpreters of narrative" (Currie, 1998, p. 2). In fact, narratives constitute "the primary form by which human experience is made meaningful" (Polkinghorne, 1988, p. 1). Sense making is key to who we are.[8]

Importantly, narratives contain plots and characters with the plot transforming a chronicle or sequence of events into a story which generates an emotional response. It is this which is necessary for, and leads to, action knitting the narrative together so we can recognize the deeper significance of the event. Stories are powerful devices for managing meaning. Through the medium of story, the unexpected can be transformed into the expectable, and the unmanageable future rendered notionally manageable or controllable. The key is a story's plausibility rather than its accuracy. Importantly, in stories unpredictability does not imply inexplicability.

"Narrative rationality, or sense making, arises from people's inherent awareness of narrative probability, what constitutes a coherent story… and narrative fidelity, whether or not the stories they experience ring true" (Fisher, 1989, p. 56). There is no requirement for them actually to be true! "Accuracy is nice but not necessary in sense making… what is necessary in sense making is a good story" (Weick, 1995, pp. 60-61).

A common feature of the myriad of financial crises and market bubbles described in Aliber and Kindleberger (2015), which range from tulip bulbs, through the South Sea Bubble, canals, railroads, stock prices before the Great Crash, real estate, internet stocks and the recent property-led financial crisis, is the presence of an emotionally-driven trajectory. In each case patchy excitement about an innovation leads to euphoria (or mania), denial (or manic defense) and then, when reality ultimately intrudes, and the bubble bursts, panic is followed finally by shame and blame. Tuckett and Taffler (2008) explore dot.com mania from a psychoanalytic perspective and demonstrate how throughout this process it is not a question of lack of information about the riskiness of the respective investments, but the way in which this is treated.[9] In parallel, Shiller (2014) argues that speculative bubbles are not about the "craziness" of investors but how they are "buffeted *en masse* from one superficially plausible theory about conventional valuation to another", i.e., by popular investment narratives which often take the form of myth.

[8] "Sense making is a search for plausibility and coherence that is reasonable and memorable, which embodies past experience and expectations, and maintains a self while resonating with others. It can be constructed retrospectively, yet used prospectively, and captures thoughts and emotions… [I]t renders the subjective something more tangible." (Weick, 1995, p. 14)

[9] Shiller (2019, p. 280) also points out how psychoanalysis can help economists understand "people, their behavior, and their thinking."

Importantly, observation of actual bubbles demonstrates how when they ultimately collapse this is not due to new facts but that the underlying reality can no longer be denied, and repressed anxieties rendered unconscious. The whole process then goes into reverse with investors now taking flight in a headlong panic. Anger and blame of others rather than feelings of personal guilt erupt allowing investors to avoid the painful realization of how they have been caught up in the temporarily very enriching and exciting wish-fulfilling fantasy. Psychologically, anxiety will change into even more painful feelings of loss, humiliation and shame for being actively involved in what has turned out to be only a chimera.

In exploring the path-dependent trajectory of an asset pricing bubble the role played by the media is key. Not only does it disseminate value-relevant information to market participants, but also provides (superficially) plausible explanations or meaning for the events as they unfold (Gamson et al., 1992). Kury (2014) claims that investors, as readers/audiences, understand financial markets through the media; in other words, investors' emotions can be influenced by the media. In parallel, media stories reflect investors' emotions as these are acted out in their investment decisions in the way in which they report on what is going on in the market (Engelberg and Parsons, 2011; Tetlock, 2011; Dougal et al., 2012; Peress, 2014; Adämmer and Schüssler 2020).

In this paper we utilize news reports, comments, opinions and press releases published in the business media to provide the popular investment narratives we work with. Specifically, we conduct formal content analysis of media reports on the stock market employing seven different emotion word dictionaries to measure market sentiments, and the interrelationships between them.

To test our thesis, we work with two market instances when the influence of economic narratives would be expected to be most pronounced. The meteoric rise in the prices of internet stocks, unexplainable in terms of fundamental value, and their equally spectacular fall, constitutes one such extreme economic event (Aggarwal et al., 2009; Bhattacharya et al., 2009). Figure 2 shows how the Dow Jones Internet Price Index rose by 1100% in just over two-and-a-half years from July 1$^{st}$ 1997, when it was launched, to March 9$^{th}$ 2000, when it peaked, compared with a 57% increase in the S&P 500. The Internet sector then accounted for 6% of the market capitalization of all US public companies and 20% of all publicly traded equity volume (Ofek and Richardson, 2003). This Index then halved in value by mid-April, and by the first anniversary of its peak was down by 85%. At the end of September 2002 it stood at only 5% of its high, even below where it was standing in July 1997.

**<<<Figure 2 here>>>**

A similar scenario was played out during the Global Financial Crisis. This time, the driver was the sharp increase in house prices in the US. Figure 3 shows how the S&P/Case-Shiller US National Home Price Index went up by almost 60% between 2002, and its peak in 2006. However, as house prices went into reverse, the S&P 500 Index collapsed, falling from 1,519 on 2nd July 2007 to 677 on 9th March 2009, a loss of 55% of its market value in a little over one-and-a-half years. This was accompanied by the most severe contraction of the US economy since the Great Depression with GDP shrinking in 5 of the 6 quarters from the first quarter of 2008. The market (and the economy) then started to recover with the S&P 500 index almost doubling by the middle of 2011 and house prices stabilizing, as Figure 3 illustrates. How can such dramatic changes in firm valuation occur across a whole sector (in the first instance) or the whole market (in the second instance) over such a short period of time?

**<<<Figure 3 here>>>**

### *2.2 Five-stage Path Dependent Emotional Trajectory during Major Market Events*

Tuckett and Taffler (2008) argue that the language conventionally used to describe such extreme market events shows they constitute an essentially emotional process.  Based on a general model of financial crises originating with Minsky (1992), Aliber and Kindleberger (2015) characterize a 3-stage model for asset pricing bubbles in terms of the path-dependent process of: initial "displacement" or some exogenous shock, "boom" and "euphoria", and then "revulsion" or "panic".

In their psychological exploration of dot.com mania, Tuckett and Taffler (2008) expand Aliber and Kindleberger's 3-stage path dependent trajectory to a 5-stage model and describe how different emotional states are salient in different phases of the bubble. As the bubble takes off, they argue investors are driven by the feelings of excitement that what they term the "phantastic object" generates which turn into a state of mania as prices shoot up faster and faster. However, concurrent with this, they point out an undercurrent of anxiety, usually not consciously acknowledged, and associated denial because on one level, investors know it is 'too good to be true'. Eventually, reality can no longer be kept at bay. Panic follows as everyone seeks to sell, followed by revulsion with the phantastic object which has now so painfully let them down, and blame (of others rather than themselves) for being caught up in the wish-fulfilling fantasy. Finally, feelings of guilt and shame, although again generally not formally acknowledged, abound.[10]

A parallel story is played out during the Global Financial Crisis when similar market-wide emotions (excitement, mania, anxiety, denial, panic, revulsion/blame and guilt) were manifest dynamically as the crisis played out. The Final Report of the Financial Crisis Inquiry Commission (FCIC, 2011) describes in detail the lack of oversight of the nonprime mortgage market as it ballooned to a total of 27 million high risk (subprime and Alt-A) mortgage loans, and how acute excitement turned into a manic demand for homes due to the cheap availability of credit. This was exploited by 'rocket scientists' in investment banks who created complex derivatives that appeared magically to transform high credit risk mortgages into what were sold as low risk securities (known as collateralized debt obligations or CDOs). Even those Wall Street bankers directly involved in the mortgage securitization process were caught up in the excitement aggressively buying larger houses and investing in second homes during the boom, and failing to anticipate the crash (Cheng, Raina, and Xiong, 2014).

On one level everyone seemed to believe house prices could continue to increase, in effect for ever, and that any associated risk could be managed. Warnings about the unsustainable inflation in house prices (e.g., the cover story of *The Economist* June 16 2005 "House Prices: After the Fall") were ignored, and any associated anxiety repressed. A good example is how Fed chairman Alan Greenspan, testifying before the Joint Economic Committee of Congress on June 9 2005, denied there would be any problem and that the system was resilient.[11] In the same way, as late as March 28 2007 after housing prices had been declining for a year, Ben Bernanke, who replaced Alan Greenspan as Fed chair, was still testifying to Congress that "the problems in the sub-prime market were likely to be contained" – that is, he again expected little spillover to the broader economy. This continuing optimism was, however, quickly followed by a collapse in the value of nonprime mortgages securitized and sold to banks around the world as borrowers started to default. Stock prices as well as house prices went into free fall in the face of a reality that could no longer be denied, and the market entered its panic phase. The S&P 500 reached its lowest point in the

[10] Aliber and Kindleberger (2015), interestingly, show how similar emotional patterns seem to dominate in most of the major speculative crises they explore which suggests common group-wide psychodynamic processes operating in the manias, panics, and economic crashes they explore throughout history.

[11] In particular, he claimed: "Nationwide banking and widespread securitization of mortgages makes it less likely that financial intermediation would be impaired than was the case in prior episodes of regional house price corrections."

middle of 2009. While house prices continued to drift down for another year, the economy began to grow again and the stock market to begin to recover. Blame inevitably then took over with the way the 634-page FCIC report seemed to be pointing its finger at everyone, almost indiscriminately, for causing the Crisis a good example.

### *2.3 Propositions*

Our main argument is that asset pricing bubbles and the associated constellation of narratives are intimately related through the powerful investor emotions they generate. If this holds, the implication is the need formally to take account of the emotions of economic agents in explanatory economic or financial models, at least of such extreme events. We set up the following four propositions to test our thesis focusing on the internet bubble and Global Financial Crisis.

First, we predict that *investor emotions and market dynamics are closely associated* with positive returns linked with ‘exciting’ emotions, and negative returns with ‘frightening’ ones. Second, as stock markets are efficient, future stock prices are essentially unpredictable and Knightian uncertainty (Knight, 1921) prevails. This inevitably leads to anxiety and associated emotions in the minds of market participants, whether acknowledged or unacknowledged, which impacts their investment decisions. We would expect such emotions to be stronger in more volatile or uncertain market conditions such as during financial crises and asset pricing bubbles, particularly as markets collapse. In contrast, underlying uncertainty will be denied in high excitement market states. Therefore, if our main contention holds, *investor emotional engagement with the market will be stronger during extreme event periods than in other periods*.

Third, during extreme market events, powerful feelings of manic excitement should lead to a rapid rise in stock prices. This process will then be reversed as soon as the bubble bursts, resulting in feelings of anxiety and panic swamping other emotions. Reflecting this emotional trajectory, again if our thesis is correct, there will be a *stronger exciting (frightening) investor emotional engagement with the market during its up (down) phase than during its collapse (expansion).*

Finally, while different popular stories will be associated with different market crises, we expect they will generate the same underlying investor emotions. Hence, we predict *the relationship between emotions and market dynamics will be similar across different types of crises in the markets.*

## 3. Data and Method

In this section, we first describe how we build the keyword dictionaries we use to measure market-wide emotions. We then present our methodology to test our propositions.

### *3.1 Dictionary Building Process*

Loughran and Mcdonald (2011) and Henry and Leone (2016) conclude that context-specific dictionaries outperform general ones. We adopt a conventional "bag-of-words" approach (Loughran and Mcdonald, 2016) in constructing our context-specific keyword dictionaries.[12] Although Loughran and McDonald (2016) argue that wordlists with associated weighting schemes may have potential benefits, Henry and Leone (2016) show that equally weighting the importance of all words performs just as well in practice as wordlists designed in more complex ways.

Based on our five-stage path-dependent emotional asset pricing trajectory, as our first step, we developed keyword dictionaries to reflect the following investor emotions which are our key variables:[13]

- Excitement
- Mania
- Anxiety
- Panic
- Revulsion/ Blame
- Denial
- Guilt

For ease of exposition, we classify the first two generically as 'exciting' emotions, and the latter five as 'frightening'.

These dictionaries are built by systematically analysing financial media reports on a monthly basis from the beginning of the internet asset pricing bubble in October 1998 through March 2000, when it burst, until October 2002. We choose to work with this period because of the highly-charged nature of the internet bubble, and the whole gamut of powerful emotions directly manifest

[12] Although specially designed dictionaries are, as Loughran and McDonald (2016) point out, often called lexicons we continue to use the term dictionaries to avoid confusion.

[13] As described above, Tuckett and Taffler (2008) explain how such investor emotions typically underlie different stages of an asset pricing bubble.

in a short period of time (e.g., Cassidy, 2002; Tuckett and Taffler, 2008). Also, this allows us to validate our dictionaries during a market crisis of a different nature occurring several years later.

In order to obtain a representative sample of media reports for dictionary development and analysis purposes, we search the Factiva database for each month from October 1998 to September 2002 using two groups of search terms:

Group 1: Technology, Internet, Computer, Com, New Economy, Web, E-commerce, Dotcom, PC, NASDAQ, Bubble

Group 2: Stock, Market, Stock Market, Share, Share Price, IPO, Crash

Articles selected for analysis need to be in English, include at least one term from both groups of search terms, and at least 500 words long.[14] We also restrict our search to US media since the dot.com bubble was largely a US phenomenon. Specifically, we draw on the three most widely circulated daily newspapers in the US (*The Wall Street Journal*, *The New York Times*, and *The Washington Post*) (Statistica, 2015), *Dow Jones Newswires*, *Barron's*, *Forbes*, and the *Financial Times*. These publications offer enough variety to provide a wide range of different stories and salient emotions as the dot.com bubble unfolded.

We first sort the articles by relevance from the most to the least mentions of our search terms, and retain only those with clear emotional content identified via direct inspection. Articles that are merely summaries of current market developments, firm reports, or already published articles are dropped from analysis.

The first 15 most relevant articles each month are used in dictionary building, and all words with a clear emotional content in these 720 articles initially tabulated. This word list is then supplemented using the pleasure, pain, excitation, emotion, moral approval, disapproval, fail, and negation categories from the merged Harvard IV General Inquirer and Lasswell Value keyword dictionaries.[15]

Appropriateness of these words for our purposes is then checked by executing a keyword-in-context (KWIC) search by scanning these 720 articles, and assessing whether the words selected resonate emotionally in our context or not. Synonyms of the words in our list are then added from the Cambridge English Dictionary.

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[14] We employ a minimum of 500 words as we found it takes roughly these many words to get a sense of what the overall text is saying.

[15] See: www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm.

Care needs to be taken when counting words based on their word roots. For example, while we need to count all pure 'rage' words as well as 'rages' and 'raged', words such as 'average', 'encourage', and 'coverage' have to be ignored. To avoid such miscounting, it is necessary to include all relevant words derived from a particular word root. In the mentioned example, instead of only taking into account 'rage', the words 'raged' and 'rages' also have to be included separately in the respective keyword dictionary. Word roots with three or fewer mentions in the 720 articles are excluded to keep our dictionaries to manageable size, and without any measurable impact on our subsequent empirical results.

We also remove words that might be used in a different context or have another meaning in the majority of the articles from our dictionaries. For example, the word 'terror' needed to be excluded as following the terrorist attacks of the 11th of September 2001 it is overwhelmingly used in this context in articles.[16]

Some words such as 'bear' and 'gamble' often appear in word combinations which are not appropriate for our analysis. 'Bear' is often used in combination with Stearns (Bear Stearns), and 'gamble' in combination with Procter (Procter & Gamble). In such cases both the word combination as well as the single word are searched for and the total word count of the word combination is subtracted from the single word count to ensure that only appearances of the word in the intended context are used in analysis. Lastly, to ensure potentially important emotion words are not missed, other potentially relevant words are added from the *Book of Human Emotions* (Smith, 2015) and then checked for their appropriateness in the context of the dot.com bubble using KWIC analysis.

This whole dictionary building process generates 251 distinct word roots with clear emotional content and relevance for our purposes. Taking into account all their different appropriate word forms results in the total of 835 keywords we employ in our textual analysis. These are provided in the on-line internet appendix A to this paper.

Finally, our root keywords are allocated to our seven emotion categories: excitement, mania, anxiety, panic, revulsion/blame, denial, and guilt. Specifically, to ensure robust and valid keyword dictionary construction each of the three authors of this paper first independently classified all the

[16] Other examples include 'revolt' (primarily used in the context of Venezuelan politics around this time), 'wonder' (used in both question and excitement contexts), and 'concern' (used both to indicate anxiety and as a company designation).

251 emotion word roots to one of our seven emotion word categories. Then, when the initial assignments differed, these differences were resolved via discussion, and reference back to the keyword-in-context analysis. Table 1 lists the five most common words in each of the seven emotion keyword dictionaries.

**<<<Table 1 here>>>**

### *3.2 Article analysis*

Since the driving forces behind the two crisis periods we explore are distinct, articles for our main textual analysis are identified for our two periods separately. For the dot.com period, we use the same criteria as those employed for dictionary building purposes.[17] However, for the Global Financial Crisis period, we use Lexis/Nexis and ABI/Inform, and limit our article search to the following keywords: “S&P”, “S&P 500”, “Standard and Poor”, “Standard and Poor 500”, and “Stock market”.[18]

### *3.3 Variable Creation*

To measure the emotional content of the financial media during the internet bubble and the Global Financial Crisis, emotions are computed as follows:[19]

$$\text{Emotion}_{i,t} = \frac{\text{Frequency of words for dictionary i in month t}}{\text{Frequency of all analyzed words in month t}} \tag{1}$$

### *3.4 Other variables*

We test our propositions by exploring the emotional impact of economic narratives on investor behavior in terms of both market return and market uncertainty, the latter we proxy for with a number of alternative variables. These are market volatility, trading volume, and the economic

[17] To reduce any potential small sample bias in our empirical results, the 150 most ‘relevant’ articles were content analyzed each month.

[18] In the case of the GFC period, we are grateful Mohammad Shehub Bin Hasan for providing our article corpus drawing on 21 different US newspapers including *USA Today* but excluding *The Financial Times*. *Dow Jones Newswires*, *Barron’s* and *Forbes* are also not accessed. In total we work with 18,453 articles from January 2004 to June 2011.

[19] We standardize by the total number of words since these vary significantly month-by-month. A higher frequency of the number of counted words in a certain category can be either due to higher emotional content or simply because more words are available in that month.

policy uncertainty (EPU) index of Baker et al. (2016). Although trading volume is conventionally viewed as a measure of trading activity (e.g., Chordia, Roll, and Subrahmanyam, 2001), or liquidity (e.g., Avramov and Chordia, 2006), Banerjee and Kremer (2010) show theoretically how disagreement between investors leads to higher volatility, and increased trading volume. Barinov (2014) shows empirically how trading volume actually proxies for uncertainty which he measures in a number of different ways. In parallel, Carlin, Longstaff, and Matoba (2014) show how asset pricing disagreements lead to increased return volatility and greater trading volume, although volatility, itself, does not result in higher trading activity save in the case of increased levels of uncertainty/disagreement. The Baker et al. (2016) EPU index is financial media news-based, and measures economic policy uncertainty directly by virtue of its construction. It is computed as the number of articles in 10 leading newspapers containing terms pertaining to uncertainty, economy, and policy, scaled by total number of articles in that month, normalized and standardized. Our main uncertainty analysis is conducted employing this time series in preference to the macro-economic focused uncertainty estimates of Jurado, Ludvigson, and Ng (2015) as this latter is derived from a large number of macro-economic and financial indicators, not narratives.[20] In the case of the internet bubble, we measure market return using the Dow Jones Internet index (DJII). Stock volatility is measured by the standard deviation of daily returns of the DJII in month t. Trading volume is calculated as the average of the daily total value of shares traded divided by end of day market capitalization of the DJII over month t.

With the Global Financial Crisis, which was economy-wide, we work with return on the S&P 500 and, in parallel, proxy uncertainty using three variables. These are VIX (the CBOE S&P 500 options-based volatility index, which is also colloquially known by other names such as 'fear gauge' or 'fear index'), trading volume measured as above save that we use the S&P 500 index instead of the DJII, and EPU.

We obtain the index data to calculate returns and standard deviation, and values of VIX from Datastream and Bloomberg. GDP data is from the Federal Reserve Bank of St. Louis website (https://fred.stlouisfed.org), and the EPU data is taken from https://www.policyuncertainty.com/us_monthly.html.

[20] However, we rerun all our analyses separately substituting Jurado et al.'s (2015) financial uncertainty, macro-economic uncertainty, and real uncertainty variables for EPU, and find similar empirical results. These are available in online appendix B.

### *3.5 Event periods examined*

We define the duration of the internet bubble period as covering the 48 months from October 1998 to September 2002. During its up phase between October 1998 and February 2000, the Dow Jones Internet index rose by 460%, reaching its peak in early March 2000. It then lost 94.0% of its value by the end of September 2002 (our down phase). We use January to April 1995 and September to December 2004, together to constitute our non-bubble (control) period as these are periods of relative calm in the market.

In the case of the Global Financial Crisis, we delineate this as lasting 66 months, from January 2006 to June 2011. Post the end of the internet bubble, and the concurrent collapse in the S&P 500, the index recovered strongly in 2003, and was then relatively flat during 2004-05 registering a gain of only 14% over this two-year period, in line with its long-term average annual return. However, it started rising strongly again from the beginning of 2006, gaining 22% over the next 18 months, even as house prices started to decline. We label the market run-up from January 2006 to June 2007, when the S&P 500 broadly peaked, as the first up phase of the GFC. The index then fell by 55% reaching its lowest point in early March of 2009, accompanied by further collapse in house prices, and the "Great Recession". We classify this period, July 2007 to February 2009, as the down phase of the GFC. Finally, the market started to recover and, by the end of June 2011, the S&P 500 had gone up over 90%. We categorize this period of market recovery as our second up phase. We consider the period from January 2004 to December 2005 as the non-crisis (control) period for this event.

### *3.6 Method*

While we would like to be able to establish a direct causal relationship between emotions on the one hand, and market returns and uncertainty on the other, this is not possible to do for several reasons. Even if causality exists it inevitably can go both ways and, in any case, is impossible to disentangle, as emotional responses to new stimuli are immediate. As Shiller (2019) points out "…new contagious narratives cause economic events, and economic events cause changed narratives" (p. 71) - Figure 1 illustrates. Therefore, we adopt a less ambitious approach and limit our analysis to exploring these synchronous relationships as being of intrinsic interest in their own right. We argue that if we want to enhance our ability to anticipate and manage major economic and market events understanding the manner in which a powerful confluence of stories generate emotions which drive investor behavior is crucial.

To test our first proposition about the relationship between emotions and market dynamics, we employ contemporaneous regressions of the form:

$$Return_t = \beta_0 + \beta_1 Emotion_t + \beta_2 Uncertainty_t + \varepsilon_t \tag{2}$$

and

$$Uncertainty_t = \beta_0 + \beta_1 Emotion_t + \beta_2 Return_t + \varepsilon_t \tag{3}$$

Where:

$Return_t$ is the return on the market index (Dow Jones Internet Index for the internet bubble period, and S&P 500 Index for the Global Financial Crisis period) during month t,

$Emotion_t$ is the standardized value (using equation (1)) of one of the seven emotions, depending upon the specification, all measured over month t.

$Uncertainty_t$ is measured in three ways: (1) The standard deviation of daily returns on the Dow Jones Internet Index during month t for the internet bubble period ($StDev_t$), or the value of the VIX index at the end of month t for the GFC period ($VIX_t$), (2) Trading volume ($Volume_t$) calculated as the average of daily total value of shares traded divided by end of day market capitalization of the DJII (dot.com), or S&P500 (GFC) index over month t, and (3) The news-based Economic Policy Uncertainty Index value ($EPU_t$) at the end of month t, obtained from www.policyuncertainty.com (based on Baker et al., 2016).

We employ the standard deviation of the DJII,[21] and its trading volume, for the first economic event we study because the phenomenon was largely restricted to internet stocks with the wider economy not directly affected in terms of overall GDP growth rate, as Figure 3 illustrates. Since the Global Financial Crisis was much more pervasive, we use S&P 500 returns, VIX, and S&P 500 trading volume in this period.[22]

To explore our second proposition about stronger emotions during periods of extreme events as compared to 'normal' market periods, we use January 1995 to April 1995 together with September

[21] We are grateful to Standard & Poor's for providing this data.

[22] We do, however, run all our tests with VIX in the dot.com period, and standard deviation of S&P 500 returns in the GFC period, and find the tenor of our conclusions remains unchanged.

2004 to December 2004 as our control (non-bubble) period in the case of dot.com mania. For the Global Financial Crisis, the equivalent control period is January 2004 to December 2005.

With respect to our third proposition about differences in emotions in the up and down phases of our two event periods, the up phase for the internet bubble is from October 1998 to February 2000, and the down phase from March 2000 to September 2002. For the Global Financial Crisis, we classify January 2006 to June 2007 in the run-up to the market and economic collapse, and March 2009 to June 2011, when the S&P 500 was recovering from its precipitous fall, as up phases and treat these together in our analysis. In parallel, the period from July 2007 to February 2009, when the S&P 500 index lost over 50% of its value, is our down phase.

Finally, we test our fourth proposition using the following OLS regressions with interaction dummies:

$$\mathrm{Return}_t = \beta_0 + \beta_1 D_t + \beta_2 \mathrm{Emotion}_t + \beta_3 \left(\mathrm{Emotion} * D\right)_t + \beta_4 \mathrm{StDev}_t + \varepsilon_t \quad (4)$$

and

$$\mathrm{Uncertainty}_t = \beta_0 + \beta_1 D_t + \beta_2 \mathrm{Emotion}_t + \beta_3 \left(\mathrm{Emotion} * D\right)_t + \beta_4 \mathrm{Return}_t + \varepsilon_t \quad (5)$$

Where:

$D_t$ = 0 for the internet bubble period and 1 for the GFC period.

All other variables are as defined before.

As variables are measured on different scales in the internet bubble and the Global Financial Crisis periods, we normalize all variables in regressions (4) and (5) by dividing them by their standard deviations over their respective periods to ensure our results are not driven by scale effects.

## 4. Results

This section provides descriptive statistics for our data and then tests each of our four propositions.

### *4.1 Descriptives*

To examine whether our emotion variables, which are determined independent of the market, are measuring underlying investor constructs, we explore their associations with market returns and uncertainty. Table 2 presents the simple correlations between emotions, market returns, and uncertainty (proxied by volatility, trading volume, and economic policy uncertainty).

In the case of the dot.com bubble period (October 1998 to September 2002), Table 2A shows that exciting emotions (excitement and mania) are positively correlated (r = 0.43) with each other, as well as with concurrent Dow Jones Internet Index monthly returns (r = 0.46 and 0.29 respectively). In parallel, frightening emotions (anxiety, panic, revulsion/blame, denial, and guilt) are all strongly positively correlated with each other (at between 0.56 and 0.78), and also have strong negative correlations with contemporaneous market returns (ranging from -0.21 to -0.49). These relationships provide preliminary evidence investor emotions and market returns are closely related.

Table 2A, similarly provides clear evidence of a strong relationship between investor emotions and market uncertainty, as measured by standard deviation of DJII returns, although only significant for the strongest frightening emotions anxiety and panic (r = 0.37; 0.30). In parallel, frightening emotions are also highly correlated with news-based economic policy uncertainty (EPU) (ranging from 0.41 to 0.76), while exciting emotions are uncorrelated with EPU. Unlike the other uncertainty proxies, trading volumes are higher when exciting emotions dominate. The limited nature of the dot.com phenomenon with respect to the broader economy is shown by the low correlation of DJII volatility and trading volume with the other uncertainty measures in the table.

Broadly speaking, table 2B provides similar results for our Global Financial Crisis period (January 2006 to June 2011) although the correlation of mania with returns is insignificant as the market up phases were relatively gentle in comparison. The relationship between frightening emotions and volatility (measured by VIX) is much stronger in this period, with most correlations exceeding 0.45. In contrast to the new economy period, all three uncertainty proxies (VIX, trading volume, and EPU) are positively and highly correlated with each other (minimum r = 0.72) showing the more pervasive market-wide nature of the Global Financial Crisis.

**<<<Tables 2A and 2B here>>>**

Our correlation analyses thus provide clear evidence consistent with our main premise that investor emotions, measured independently using media narratives, are closely associated with both market returns and different measures of market uncertainty.

To explore our main proposition that there is a relationship between economic narratives and market behavior mediated by the emotions they generate, we test the extent to which our seven salient emotions taken together help explain market pricing. Table 3 presents the results of regressing market returns, volatility, trading volume, and EPU separately against our seven emotion variables jointly. Panel A reports respective adjusted $R^2$s for each regression for the internet bubble period, and panel B the equivalent for the Global Financial Crisis. All adjusted $R^2$s are significant at $p<0.01$, and six out of the eight in the two panels are 40% or above, with the other two also very large. Perhaps of most interest is that in the case of the internet bubble emotions inherent in media stories explain 40% of market returns, and for the GFC, 37%. These results are consistent with our main thesis.

<<<**Table 3 here**>>>

*4.2 Relationship between investor emotions and market dynamics*

How are different emotions linked to market movements? To explore their association with market returns and market uncertainty in the two periods Table 4 reports the emotion variable coefficients in regressions (2) and (3).[23] Panel A presents our results for the new economy bubble period, and Panel B for the Global Financial Crisis. Panel A row (1) shows that exciting emotions have a strong positive association with contemporaneous returns (t = 3.7 and 2.1 for excitement and mania respectively) even after controlling for level of uncertainty as measured by the standard deviation of DJII returns (market volatility). In parallel, frightening emotions (with the exception of denial) have a strong negative relationship with returns. Row (2) shows only excitement (t = 1.9), anxiety (t = 3.0) and panic (t = 2.1) are associated with the standard deviation of DJII returns, while row (3) shows only excitement (t = 3.5) and guilt (t = -2.2) have a significant relationship with trading volume. Finally, row (4) shows a strong relationship between frightening emotions and the policy uncertainty measure EPU.

<<<**Table 4 here**>>>

[23] Intercepts and the control variable coefficients are not reported for parsimony reasons.

In the case of the GFC, Table 4 panel B row (1) shows a weaker relationship between emotions and returns. While excitement is strongly associated with returns (t = 2.9), mania is not. For the frightening emotions, we find panic is strongly and negatively associated with returns (t = 4.1), but denial and guilt are both only significant at the 10% level. Row (2) presents parallel results regressing VIX against investor emotion variables. This shows that while exciting emotions are not related with VIX, frightening emotions (except guilt) are strongly, and positively, associated with uncertainty demonstrating the powerful frightening emotions salient during periods of high market volatility. Rows (3) and (4) show similar results for both trading volume and EPU.

Consistent with our first proposition, Table 4 demonstrates how different emotions salient in the media are important in explaining market behavior, at least in the crisis periods we examine. Specifically, we show that exciting emotions have a positive relationship with returns, while frightening emotions have a negative relationship. Further, during the Global Financial Crisis, we find that market uncertainty and frightening emotions are closely linked with a similar, although slightly attenuated, relationship pertaining during the internet bubble.

### *4.3 Investor engagement during extreme market events*

To test our second proposition that investor emotions are more powerful in extreme market conditions, we compare our emotion variables during the dot.com bubble and the Global Financial Crisis periods with their non-crisis values. Table 5 presents the standardized mean values of our emotion variables for the two periods and their respective control periods in panel A, and the equivalent uncertainty measures in panel B. Columns (1) to (4) of panel A show that all our seven emotions are much more powerful during dot.com mania compared with non-mania periods (all differences significant at better than $p = 0.001$). This demonstrates how highly charged emotions and investor trading behavior are closely linked during this market episode. Parallel high levels of market turmoil and associated uncertainty are observed in panel B as measured by increased market volatility and higher trading volume, as well as greater economic policy uncertainty. However, results not tabulated show growth rate of Real GDP during the internet bubble is virtually identical to that in the control period, demonstrating the relatively limited impact of the dot.com bubble on the broader economy.

Columns (5) to (8) of Table 5 present parallel results for the Global Financial Crisis. With the exception of mania and denial, all other emotions differ significantly during the Crisis compared to the pre-crisis control period. Again, market turmoil is clearly evident as reflected in much higher volatility (as measured by VIX), higher trading volume, and greater policy uncertainty (measured by EPU). The much broader impact of the Global Financial Crisis on the underlying economy is also clear with the GDP growth rate during this period significantly lower than during the control period (t = 6.1 in untabulated results). We conclude that the results presented in Table 5 strongly support our second proposition; extreme market events are clearly highly emotional episodes compared with non-crisis periods.

**<<<Table 5 here>>>**

*4.4 Investor emotions in the up and down phases of a market bubble*

We compare investor emotions in our extreme market conditions to test our third proposition that positive (negative) emotional engagement is more (less) salient when markets go up, and less (more) salient as they collapse. Table 6 compares emotions, and level of uncertainty, across the growth and contraction phases of our two market crisis periods. In the case of the internet bubble columns (1) to (4) of panel A clearly show, not surprisingly, excitement is much higher as new economy stock prices shoot up, while frightening emotions predominate after the bubble bursts. Panel B shows that while volatility (standard deviation of the Dow Jones Internet Index) does not differ in the up and down phases of the new economy bubble, trading volumes are much higher in the up phase consistent with market participants becoming caught up in the excitement. Economic policy uncertainty is much more manifest after the bubble bursts.

In the case of the Global Financial Crisis, columns (5) to (8) of panel A of Table 6 show how investor excitement is much greater as the market rises up to its peak (January 2006 to June 2007), and during its recovery from its nadir (March 2009 to June 2011). This compares with its contraction phase (July 2007 to February 2009). Not surprisingly, anxiety, panic, and revulsion/blame are much stronger during the economic recession. However, panel B, presents a different picture to the new economy bubble. In this case, volatility (as measured by VIX) is much higher during the crisis period, highlighting how uncertainty and frightening emotions are intimately linked. Similarly, trading volume is much greater as the market collapses, possibly reflecting panic selling.[24] As with dot.com mania, policy uncertainty is higher during the down phase of the Global Financial Crisis.

**<<<Table 6 here>>>**

Table 6 clearly supports our third proposition showing that exciting emotions are stronger during up phases and frightening emotions during the down phases of extreme market events. Overall, our empirical findings are again consistent with our main thesis that economic narratives reflect investor emotions, and these are an integral part of market activity.

### *4.5 Does the relationship between the emotions generated by different narratives, and market dynamics differ in the two crisis periods?*

Finally, we test our fourth proposition that investor emotions, measured through textual analysis of financial media, play similar roles during different extreme market events. Table 7 presents the results.[25] Column (2) across all panels again shows clearly that stock market investors are highly emotional in their engagement with the stock market, at least during the two crisis periods we examine. Perhaps more interesting, however, is how, broadly speaking, the relationship between investor emotions and market returns is virtually identical in both the internet bubble and the Global Financial Crisis periods as the lack of statistical significance of the emotion/period dummy interaction term ($\beta_3$) in panel A illustrates. On the other hand, we do find in panel B that the relationship of volatility with excitement is weaker during the GFC while that with panic and revulsion/blame is more salient. The evidence of differences between the two periods in investors' emotional responses to uncertainty is even stronger in the case of trading volume as panel C indicates. We speculate these latter findings may reflect the more speculative and less all-encompassing nature of dot.com mania (Cassidy, 2002) compared with the high levels of market and economic uncertainty during the GFC as reflected in the significance of the $\beta_3$ coefficients for our frightening emotions, anxiety, panic, revulsion/blame, denial and guilt. Panel D demonstrates,

[24] We speculate that the differences between the two crises might be reflecting that in the dot.com case there were no buyers as many of these stocks were effectively worthless, whereas in the case of the GFC, stocks were fundamentally viable in most cases, but simply 'worth less'.

[25] Intercepts and the control variable coefficients are not reported for parsimony reasons.

however, the relationship between EPU and investor emotions does not differ between the two periods. This may relate to how this variable is measuring different dimensions of economic policy and associated uncertainties rather than stock market related volatility and trading volumes directly.

**<<<Table 7 here>>>**

## 5. Discussion and Conclusion

In his book *Narrative Economics*, Shiller (2019) describes the key role economic narratives play in helping to explain important economic events. However, he cautions against assuming that economic events always drive economic narratives, and argues (p. 75) "contagious stories are largely creative and innovative, not simply a logical reaction to economic events". In this paper, we argue the power of economic narratives resides in the emotions they generate which provoke spontaneous and powerful responses in line with System 1 intuitive and reflexive mental processes (e.g., Kahneman, 2012).

Investor emotions are key determinants of market pricing. The extreme market volatility associated with the recent COVID-19 pandemic dramatically illustrates the role these play in driving market behavior. The S&P 500 index peaked on 19 February 2020 after a run-up of 400% over the previous 11 years, even though the threat COVID-19 represented was already well known. The VIX was then standing at only 15%, similar to that in previous years. However, stock market fluctuations over the following few weeks are difficult to explain in rational terms with average S&P 500 daily volatility (measured as (high – low)/(average of high and low)) of 4.6%, with the VIX hovering around 60%-80% to the end of March when the market started to recover, even higher than at the peak of the Global Financial Crisis. Such day-to-day fluctuations are unlikely to be explained by changes in valuation expectations. Clearly, a more plausible explanation is that a whole raft of emotions as reflected in news coverage and commentary in the mass media were driving investor behavior, including anxiety, panic, and denial, seemingly changing from one moment to the next.

In this paper, we show that investor emotions are a key factor in market pricing. Our empirical analysis demonstrates how in seeking to understand the etiology of, *inter alia*, asset pricing bubbles, and manage these more effectively, we need to explore more formally the underlying emotional processes at work, and their drivers. In particular, focusing on two episodes of extreme market movements, the internet bubble, and the Global Financial Crisis, we show how popular narratives published in the media generate powerful emotions which help explain investor behavior, and consequently market dynamics.

Specifically, we adopt formal textual analysis of financial media narratives to measure the relative strengths of a range of different market emotions derived from psychological theory as they change dynamically during our crisis events. We provide evidence consistent with our main thesis that economic narratives, investor emotions, and market prices are intimately linked. We demonstrate the power emotions reflected in popular stories have to explain contemporaneous market returns, and market uncertainty. Investor emotions together can explain up to 40% of monthly market returns and around two thirds of market uncertainty. As expected, narratives that provoke exciting emotions dominate in the up phase of a bubble, and frightening ones after it bursts.

In addition, we find economic narratives generate stronger emotions during extreme market events such as those we explore here. Interestingly, we also show that the relationship with market returns of the key investor emotions we measure is equally strong in the two crisis periods we explore. However, the strength of the emotional resonance market uncertainty has for investors as measured by our anxiety, panic, revulsion/blame, denial and guilt metrics is much stronger in the case of the Global Financial Crisis than the internet bubble, reflecting its all-encompassing nature.

Our paper adds to the nascent literature on narrative economics, as well as seeking to increase understanding of the morphology of financial crises in general. First, it suggests that in seeking to explain asset pricing bubbles formal models could usefully take into account the emotions stories propagated, *inter alia* in the financial media, create. Our empirical evidence clearly suggests these are key determinants of market behavior, at least during such extreme market events as we explore here. Second, methodologically we demonstrate how it is possible to measure different market emotions directly through systematic analysis of economic narratives. Third, we construct original context-dependent emotion keyword dictionaries which are novel in the literature and have the potential for wider application, and show how such simple bag-of-words approaches can be powerful in the analysis of economic narratives. We also demonstrate how our emotion keyword dictionaries constructed using one major market bubble work equally well when used to analyze a very different financial crisis almost a decade later. This evidence is also consistent with the idea that such extreme market events manifest similar path-dependent emotional trajectories more generally in line with Aliber and Kindleberger (2015). Finally, we show how market uncertainty is associated with high levels of anxiety, panic, and related emotions which can be empirically measured.

Our results also open up a number of interesting areas for further research. These include analysing other stock market bubbles such as the two recent Chinese episodes, in a parallel way, property bubbles such as those in Ireland and Japan, and other types of asset pricing bubble more generally. We also speculate a similar psychological perspective could help shed light on the market reaction to other global crises, including pandemics as with COVID-19 currently, and related issues. Andrade et al., (2016) and Breaban and Noussair (2018) create experimental asset markets designed to generate asset pricing bubbles and confirm how emotions and market dynamics are closely related. Our findings suggest the opportunity for developing experimental markets with greater verisimilitude which might include introducing economic narratives into the experimental design to allow more detailed investigation of the joint role played by stories and emotions in determining investor behavior.

Lastly, importantly, we demonstrate that in seeking to understand the role played by potentially different and conflicting narratives in major economic events, it is not necessary to have to employ a large number of carefully trained research assistants to analyze and classify these directly as Shiller (2019) suggests in his final chapter. We recognize, as Shiller illustrates, how individual stories may be highly entertaining and of intrinsic interest in their own right. However, by explicitly focusing on, and formally measuring, the different emotions a constellation of narratives generates in the minds of economic agents, we show how it is possible to disentangle the emotions an often complex and contradictory web of stories trigger, and their relationship with market dynamics.

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**Figure 1: Interrelationships between narratives, emotions, and market behavior**

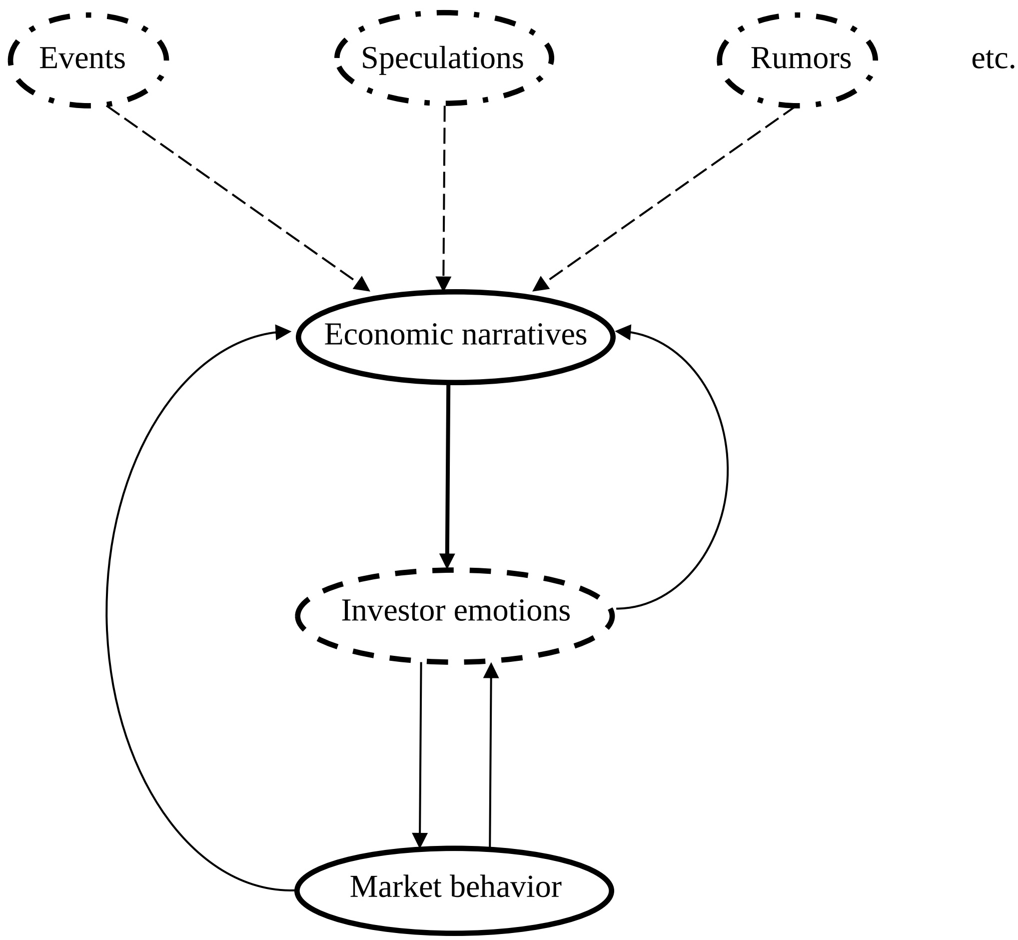
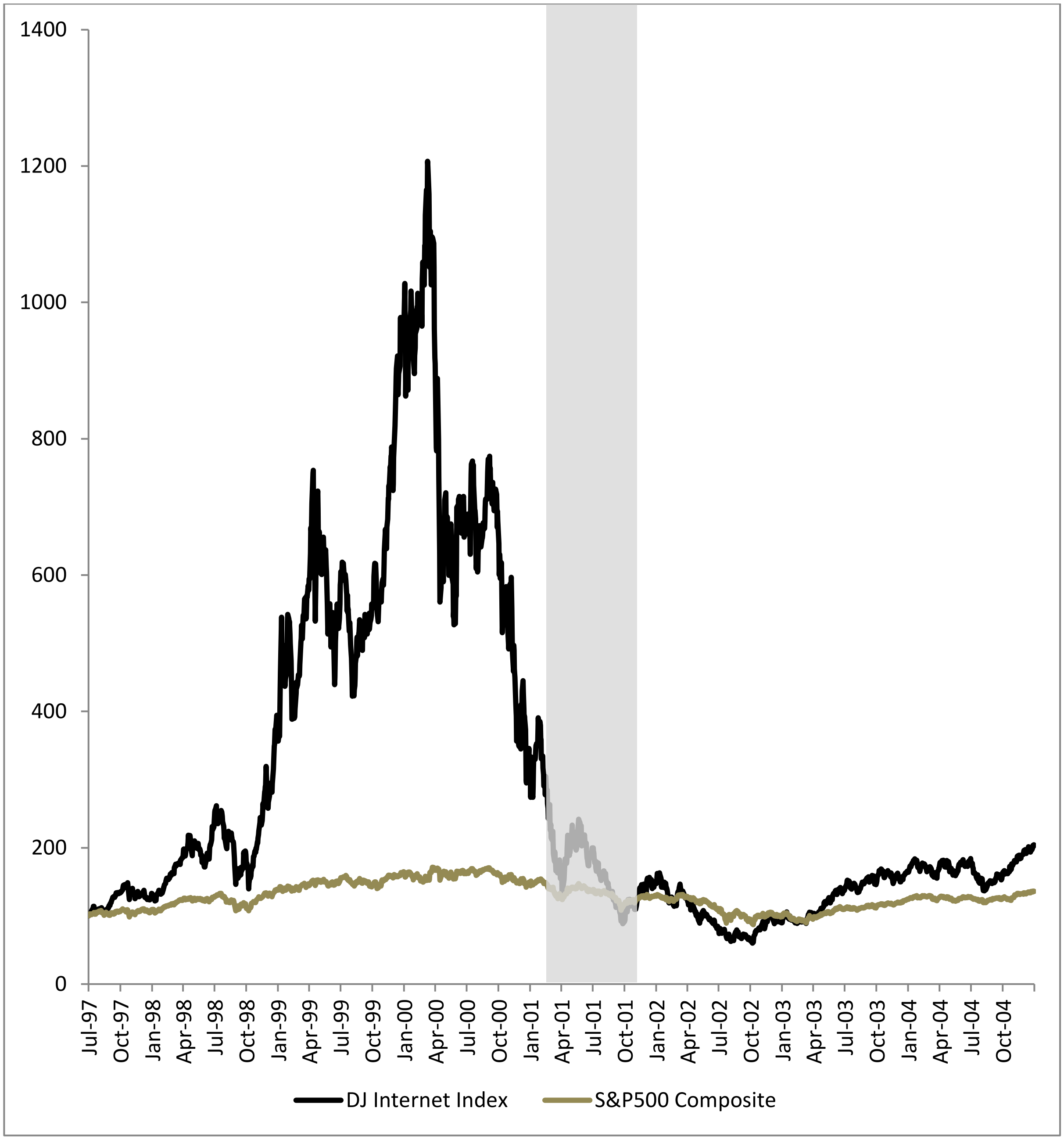
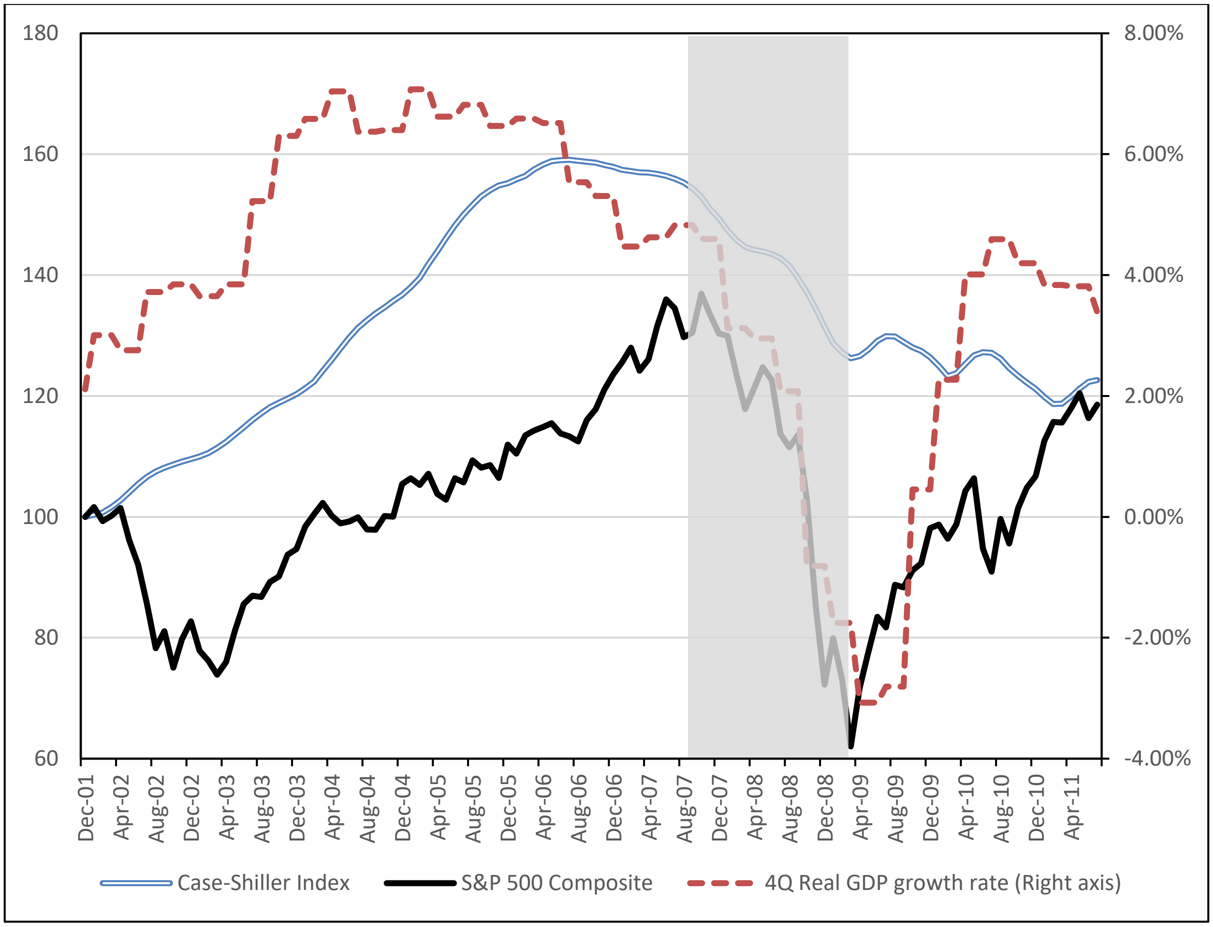


**Figure 2 – Dow Jones Internet Index and S&P 500 Composite (July 1997 to December 2004) (rebased to 100)**




*Notes:* The shaded period is the NBER recession period (Mar-01 to Nov-01).

**Figure 3 – The S&P/Case-Shiller National Home Price Index, S&P 500 Composite (rebased to 100), and trailing four quarters' real GDP growth rate (January 2002 to June 2011)**




*Notes:* The shaded period is the NBER recession period (Dec-07 to Jun-09).

**Table 1: Five most common words in each keyword emotion category**

| | % of Category |
|---|---|
| **A. Excitement** | |
| Bull | 10.17 |
| Success | 9.39 |
| Rise | 9.06 |
| Double | 6.58 |
| Expand | 6.51 |
| **B. Mania** | |
| Bubble | 15.87 |
| Huge | 13.47 |
| Boom | 11.44 |
| Gigantic | 6.31 |
| Wave | 4.21 |
| **C. Anxiety** | |
| Fall | 16.20 |
| Risk | 12.04 |
| Worry | 6.10 |
| Difficult | 5.89 |
| Volatile | 5.12 |
| **D. Panic** | |
| Drop | 19.92 |
| Collapse | 8.27 |
| Trouble | 7.76 |
| Drama | 7.72 |
| Crash | 7.48 |
| **E. Revulsion/Blame** | |
| Failure | 11.55 |
| Recession | 8.45 |
| Suffer | 7.47 |
| Wrong | 6.90 |
| Bankrupt | 6.55 |
| **F. Denial** | |
| Hope | 31.80 |
| Warning | 20.18 |
| Defend | 13.45 |
| Ignorance | 8.99 |
| Refusal | 3.51 |
| **G. Guilt** | |
| Damage | 28.13 |
| Burn | 25.06 |
| Cry | 10.49 |
| Regret | 6.14 |
| Confess | 5.12 |

## Table 2A: Correlation matrix: Emotions, market returns, and uncertainty – Internet bubble

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Excitement | 1 | | | | | | | | | | | | |
| (2) Mania | 0.43*** | 1 | | | | | | | | | | | |
| (3) Anxiety | -0.25* | 0.14 | 1 | | | | | | | | | | |
| (4) Panic | -0.27* | 0.19 | 0.78*** | 1 | | | | | | | | | |
| (5) Revulsion | -0.4*** | 0.25* | 0.62*** | 0.71*** | 1 | | | | | | | | |
| (6) Denial | -0.41*** | -0.01 | 0.63*** | 0.55*** | 0.48*** | 1 | | | | | | | |
| (7) Guilt | -0.47*** | 0.08 | 0.56*** | 0.51*** | 0.56*** | 0.53*** | 1 | | | | | | |
| (8) $Ret_{t+1}$ | 0.25* | 0.17 | -0.06 | 0.07 | -0.16 | -0.15 | -0.15 | 1 | | | | | |
| (9) $Ret_t$ | 0.46*** | 0.29** | -0.49*** | -0.31** | -0.34** | -0.21 | -0.30** | 0.16 | 1 | | | | |
| (10) $Ret_{t-1}$ | 0.42*** | 0.10 | -0.48*** | -0.29** | -0.27* | -0.46*** | -0.55*** | 0.19 | 0.18 | 1 | | | |
| (11) $StDev_t$ | 0.24 | 0.14 | 0.37*** | 0.30** | -0.07 | 0.22 | 0.10 | 0.01 | -0.02 | 0.00 | 1 | | |
| (12) $VIX_t$ | 0.20 | 0.30** | 0.53*** | 0.53*** | 0.29** | 0.15 | 0.19 | 0.37*** | -0.20 | -0.10 | 0.21 | 1 | |
| (13) $Volume_t$ | 0.59*** | 0.25* | -0.17 | 0.00 | -0.34** | -0.18 | -0.41*** | 0.18 | 0.51*** | 0.28* | 0.48*** | 0.12 | 1 |
| (14) $EPU_t$ | -0.22 | -0.05 | 0.53*** | 0.76*** | 0.46*** | 0.41*** | 0.45*** | 0.21 | -0.10 | -0.27* | 0.18 | 0.56*** | 0.13 |

*Notes:* Standardized emotions are estimated each month from October-1998 to September-2002. $Return_t$, $Return_{t-1}$, and $Return_{t+1}$ are the return on the Dow Jones Internet Index (DJII) during the same month, previous month, and subsequent month, respectively. $StDev_t$, is the standard deviation of daily returns on the DJII during month t, $VIX_t$ is the value of the VIX index at the end of month t, $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII in month t, and $EPU_t$ is the news-based Economic Policy Uncertainty Index value at the end of month t obtained from www.policyuncertainty.com (based on Baker et al. 2016). *,** and *** denote significant at the 10%, 5% and 1% levels.

**Table 2B: Correlation matrix: Emotions, market returns, and uncertainty – Global Financial Crisis**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Excitement | 1 | | | | | | | | | | | | |
| (2) Mania | 0.21* | 1 | | | | | | | | | | | |
| (3) Anxiety | -0.02 | -0.18 | 1 | | | | | | | | | | |
| (4) Panic | -0.47*** | -0.18 | 0.66*** | 1 | | | | | | | | | |
| (5) Revulsion | -0.40*** | -0.10 | 0.46*** | 0.54*** | 1 | | | | | | | | |
| (6) Denial | -0.31*** | 0.03 | 0.22* | 0.21* | 0.51*** | 1 | | | | | | | |
| (7) Guilt | -0.35*** | 0.03 | 0.17 | 0.38*** | 0.09 | 0.10 | 1 | | | | | | |
| (8) $Ret_{t+1}$ | 0.29** | 0.06 | 0.03 | -0.30** | -0.17 | -0.04 | -0.13 | 1 | | | | | |
| (9) $Ret_t$ | 0.43*** | 0.17 | -0.36*** | -0.62*** | -0.40*** | -0.05 | -0.25** | 0.29** | 1 | | | | |
| (10) $Ret_{t-1}$ | 0.25** | 0.08 | -0.39*** | -0.42*** | -0.32*** | -0.01 | -0.18 | -0.04 | 0.29** | 1 | | | |
| (11) $StDev_t$ | -0.36*** | -0.11 | 0.61*** | 0.74*** | 0.64*** | 0.42*** | 0.24** | -0.23* | -0.53*** | -0.56*** | 1 | | |
| (12) $VIX_t$ | -0.28** | -0.04 | 0.59*** | 0.67*** | 0.72*** | 0.45*** | 0.10 | -0.10 | -0.48*** | -0.47*** | 0.92*** | 1 | |
| (13) $Volume_t$ | -0.28 | -0.07 | 0.63*** | 0.70*** | 0.71*** | 0.46*** | 0.09 | -0.11 | -0.38*** | -0.32*** | 0.82*** | 0.88*** | 1 |
| (14) $EPU_t$ | -0.33*** | -0.10 | 0.42*** | 0.62*** | 0.60*** | 0.30** | 0.14 | -0.21* | -0.33*** | -0.33*** | 0.67*** | 0.73*** | 0.72*** |

*Notes:* Standardized emotions are estimated every month from Jan-2006 to June-2011. $Return_t$, $Return_{t-1}$, and $Return_{t+1}$ are the return on the S&P 500 Composite Index during the same month, previous month, and subsequent month, respectively. $StDev_t$, is the standard deviation of daily returns on the index during month t, $VIX_t$ is the value of the VIX index at the end of month t, $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite Index in month t, and $EPU_t$ is the news-based Economic Policy Uncertainty Index value at the end of month t obtained from www.policyuncertainty.com (based on Baker et al., 2016). *,** and *** denote significant at the 10%, 5% and 1% levels.

**Table 3: Contemporaneous regression: Emotions, market returns, and uncertainty during the internet bubble and the Global Financial Crisis**

| Dependent variable | Adj $R^2$ | p |
|---|---|---|
| **A. Internet bubble period (Oct-98 to Sep-02)** | | |
| $Return_t$ | 0.40 | 0.00 |
| $StDev_t$ | 0.29 | 0.00 |
| $Volume_t$ | 0.46 | 0.00 |
| $EPU_t$ | 0.61 | 0.00 |
| **B. The Global Financial Crisis period (Jan-06 to Jun-11)** | | |
| $Return_t$ | 0.37 | 0.00 |
| $VIX_t$ | 0.65 | 0.00 |
| $Volume_t$ | 0.69 | 0.00 |
| $EPU_t$ | 0.43 | 0.00 |

*Notes:* The table reports the adjusted $R^2$s of the following OLS regressions:

$$Y_t = \beta_0 + \sum(\beta_n Emotion_{n,t}) + \varepsilon_t$$

Where $Y_t$ is the $Return_t$, $StDev_t$ (in panel A), $VIX_t$ (in panel B), $Volume_t$, or $EPU_t$, depending on the specification. $Return_t$ is the return on the Dow Jones Internet Index (DJII) during month t in panel A, and the return on the S&P 500 Composite index during month t in panel B, $StDev_t$, is the standard deviation of daily returns on the DJII during month t, $VIX_t$ is the value of the VIX index at the end of month t, $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII over month t in panel A, and the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t in panel B. $EPU_t$ is the news-based Economic Policy Uncertainty Index value obtained from www.policyuncertainty.com (based on Baker et al., 2016). $Emotion_{n,t}$ is measured at the end of month t and represents the standardized value of each of the seven (n) emotions. p refers to the p-values of the overall F-statistics of the individual regressions.

**Table 4: Contemporaneous regressions: Emotions, market returns, and uncertainty**

| | Excitement | Mania | Anxiety | Panic | Revulsion/Blame | Denial | Guilt |
|---|---|---|---|---|---|---|---|
| **Panel A: The internet bubble period (Oct-98 to Sep-02)** | | | | | | | |
| (1) Return | 2.20 | 1.57 | -1.75 | -1.66 | -1.21 | -2.26 | -8.34 |
| | (3.66) | (2.07) | (-4.06) | (-2.29) | (-2.42) | (-1.42) | (-2.12) |
| (2) StDev | 1.77 | 1.09 | 1.87 | 2.02 | -0.42 | 3.02 | 3.47 |
| | (1.95) | (1.07) | (3.04) | (2.19) | (-0.59) | (1.51) | (0.64) |
| (3) Volume | 1.99 | 0.57 | 0.31 | 0.86 | -0.67 | -0.79 | -7.89 |
| | (3.48) | (0.82) | (0.68) | (1.33) | (-1.41) | (-0.57) | (-2.24) |
| (4) EPU | -2.02 | -0.19 | 4.12 | 8.33 | 3.56 | -0.79 | 26.48 |
| | (-1.32) | (-0.11) | (4.40) | (8.18) | (3.38) | (-2.90) | (3.27) |
| **Panel B: The Global Financial Crisis period (Jan-06 to Jun-11)** | | | | | | | |
| (1) Return | 6.74 | 13.99 | -1.95 | -11.31 | -5.37 | 27.72 | -83.31 |
| | (2.93) | (1.36) | (-0.91) | (-4.11) | (-0.71) | (1.74) | (-1.90) |
| (2) StDev | -4.30 | 8.15 | 16.00 | 26.82 | 63.97 | 120.57 | -22.34 |
| | (-0.78) | (0.36) | (4.64) | (5.06) | (6.92) | (4.46) | (-0.23) |
| (3) Volume | -0.33 | -0.06 | 1.00 | 1.77 | 3.49 | 6.47 | -0.10 |
| | (-1.10) | (-0.05) | (5.58) | (6.72) | (6.86) | (4.33) | (-0.02) |
| (4) EPU | -0.45 | -0.36 | 0.50 | 1.29 | 2.44 | 3.35 | 2.20 |
| | (-1.81) | (-0.35) | (2.92) | (5.37) | (5.15) | (2.46) | (0.48) |

*Notes:* The table reports the results of OLS regressions models (2) and (3). Emotions are measured at the end of each month, and are standardized using equation (1). $Return_t$ is the return on the Dow Jones Internet Index (DJII) during month t in panel A and return on the S&P 500 Composite index during month t in panel B. $StDev_t$, is the standard deviation of daily returns on the DJII during month t in panel A, and the value of the CBOE volatility index (VIX) at the end of month t in panel B. $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII in month t in panel A, and the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t in panel B. $EPU_t$ is the news-based Economic Policy Uncertainty Index value obtained from www.policyuncertainty.com (based on Baker et al., 2016). Numbers in parentheses are the t-statistics. Intercepts and coefficients on control variables are not reported for brevity.

**Table 5: Mean emotions and uncertainty measures during extreme market events and associated control periods**

| | Internet bubble period | | | | Global Financial Crisis period | | | |
|---|---|---|---|---|---|---|---|---|
| | Bubble period (1) | Control period (2) | Difference in means (3) | t (4) | GFC period (5) | Control period (6) | Difference in means (7) | t (8) |
| **A. Emotions** | | | | | | | | |
| Excitement | 0.366 | 0.330 | 0.036 | (5.38) | 2.362 | 2.427 | -0.066 | (-2.29) |
| Mania | 0.165 | 0.114 | 0.051 | (9.01) | 0.227 | 0.219 | 0.008 | (1.26) |
| Anxiety | 0.358 | 0.284 | 0.074 | (7.78) | 1.756 | 1.510 | 0.246 | (6.38) |
| Panic | 0.156 | 0.122 | 0.034 | (5.49) | 0.682 | 0.481 | 0.201 | (6.90) |
| Revulsion/Blame | 0.183 | 0.154 | 0.029 | (3.45) | 0.356 | 0.311 | 0.046 | (3.58) |
| Denial | 0.099 | 0.084 | 0.015 | (5.45) | 0.159 | 0.161 | 0.002 | (-0.35) |
| Guilt | 0.023 | 0.020 | 0.004 | (3.38) | 0.027 | 0.038 | -0.010 | (-6.89) |
| **B. Uncertainty** | | | | | | | | |
| $StDev_t$ | 0.698 | 0.243 | 0.455 | (12.05) | 22.915 | 14.119 | 8.797 | (6.77) |
| $Volume_t$ | 0.674 | 0.303 | 0.371 | (12.38) | 1.990 | 1.079 | 0.910 | (13.48) |
| $EPU_t$ | 1.126 | 0.957 | 0.169 | (2.68) | 112.659 | 81.203 | 31.456 | (5.66) |

*Notes:* The internet bubble period is from Oct-1998 to Sep-2002 with Jan-1995 to Apr-1995 and Sep-2004 to Dec-2004 as its control period. The Global Financial Crisis (GFC) period is from Jan-2006 to Jun-2011 with Jan-2004 to Dec-2005 as its control period. Emotions are measured at the end of each month, and are standardized using equation (1). $StDev_t$, is the standard deviation of daily returns on the Dow Jones Internet Index (DJII) during month t for the internet bubble period, and the value of the VIX index at the end of month t for the GFC period. $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII over month t for the internet bubble period, and and the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t for the GFC period. $EPU_t$ is the news-based Economic Policy Uncertainty Index value at the end of month t obtained from www.policyuncertainty.com (based on Baker et al., 2016). The table presents the t-statistics for test of difference in means. Since the data for the Dow Jones Internet Index is only available from July-1997, the control period for StDev and Volume is from Sep-2004 to Dec-2004. For ease of exposition, market emotion means and differences, and Volume are multiplied by 100.

**Table 6: Tests of differences in mean emotions and uncertainty in the up and down phases of our crisis periods**

| | **Internet bubble period** | | | | **Global Financial Crisis period** | | | |
|---|---|---|---|---|---|---|---|---|
| | Up phase (1) | Down phase (2) | Difference in mean (3) | t (4) | Up phase (5) | Down phase (6) | Difference in mean (7) | t (8) |
| **A. Emotions** | | | | | | | | |
| Excitement | 0.411 | 0.342 | 0.069 | (7.06) | 2.427 | 2.212 | 0.215 | (3.80) |
| Mania | 0.178 | 0.158 | 0.019 | (1.65) | 0.235 | 0.209 | 0.026 | (1.85) |
| Anxiety | 0.310 | 0.384 | -0.074 | (-4.38) | 1.665 | 1.964 | -0.299 | (-3.94) |
| Panic | 0.127 | 0.171 | -0.045 | (-4.02) | 0.602 | 0.867 | -0.265 | (-4.85) |
| Revulsion/Blame | 0.136 | 0.208 | -0.072 | (-5.03) | 0.322 | 0.435 | -0.113 | (-4.65) |
| Denial | 0.084 | 0.107 | -0.024 | (-4.89) | 0.156 | 0.167 | -0.011 | (-1.14) |
| Guilt | 0.016 | 0.027 | -0.011 | (-6.20) | 0.026 | 0.030 | -0.004 | (-1.18) |
| **B. Uncertainty** | | | | | | | | |
| $StDev_t$ | 0.704 | 0.694 | 0.010 | (0.12) | 19.856 | 29.953 | -10.097 | (-3.96) |
| $Volume_t$ | 0.825 | 0.591 | 0.234 | (4.39) | 1.843 | 2.329 | -0.486 | (-3.60) |
| $EPU_t$ | 87.567 | 126.280 | -38.712 | (-3.22) | 104.710 | 130.942 | -26.232 | (-2.23) |

*Notes:* The period from Oct-1998 to February-2000 is the up phase of the internet bubble period, and from Mar-2000 to Sep-2002 its down phase. For the Global Financial Crisis (GFC), Jan-06 to Jun-07 and Mar-09 to Jun-11 are the up phases, while Jul-07 to Feb-09 is the down phase. Emotions are measured at the end of each month, and are standardized using equation (1). $StDev_t$, is the standard deviation of daily returns on the Dow Jones Internet Index (DJII) during month t for the internet bubble period, and the value of the VIX index at the end of month t for the GFC period. $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII over month t for the internet bubble period, and the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t for the GFC period. $EPU_t$ is the news-based Economic Policy Uncertainty Index value at the end of month t obtained from www.policyuncertainty.com (based on Baker et al., 2016). The table presents the t-statistics for the two-sample test of difference. For ease of exposition, emotion mean differences, and Volume are multiplied by 100.

**Table 7: Relationship between emotions and market behavior in the two crisis periods**

| | $\beta_1$ | t | $\beta_2$ | t | $\beta_3$ | t |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A.** $\mathbf{Return_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 StDev_t + \varepsilon_t}$ | | | | | | |
| Excitement | 0.58 | (0.38) | 0.53 | (4.12) | -0.18 | (-1.05) |
| Mania | 0.66 | (0.84) | 0.33 | (2.42) | -0.18 | (-0.98) |
| Anxiety | -0.74 | (-0.75) | -0.45 | (-3.21) | 0.15 | (0.86) |
| Panic | 0.70 | (1.18) | -0.31 | (-2.39) | -0.30 | (-1.77) |
| Revulsion/Blame | -0.20 | (-0.29) | -0.35 | (-2.59) | 0.09 | (0.44) |
| Denial | -1.14 | (-1.26) | -0.14 | (-0.99) | 0.23 | (1.22) |
| Guilt | -0.39 | (-0.74) | -0.28 | (-2.01) | 0.05 | (0.29) |
| **Panel B.** $\mathbf{StDev_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | 4.04 | (2.52) | 0.39 | (2.71) | -0.53 | (-2.97) |
| Mania | 0.47 | (0.58) | 0.24 | (1.66) | -0.22 | (-1.22) |
| Anxiety | -1.83 | (-1.97) | 0.32 | (2.38) | 0.23 | (1.37) |
| Panic | -1.31 | (-2.28) | 0.30 | (2.34) | 0.36 | (2.20) |
| Revulsion/Blame | -3.14 | (-5.75) | -0.13 | (-1.01) | 0.79 | (4.92) |
| Denial | -1.49 | (-1.77) | 0.17 | (1.25) | 0.27 | (1.58) |
| Guilt | -0.49 | (-0.90) | 0.01 | (0.08) | 0.01 | (0.07) |
| **Panel C.** $\mathbf{Volume_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | 7.78 | (4.96) | 0.62 | (4.39) | -0.87 | (-4.96) |
| Mania | 1.73 | (2.07) | 0.26 | (1.72) | -0.32 | (-1.67) |
| Anxiety | -4.06 | (-4.33) | -0.12 | (-0.88) | 0.79 | (4.73) |
| Panic | -1.90 | (-3.49) | 0.10 | (0.86) | 0.81 | (5.17) |
| Revulsion/Blame | -3.16 | (-5.91) | -0.30 | (-2.41) | 1.05 | (6.73) |
| Denial | -2.47 | (-2.82) | -0.18 | (-1.29) | 0.64 | (3.53) |
| Guilt | -1.12 | (-2.04) | -0.43 | (-2.96) | 0.51 | (2.73) |
| **Panel D.** $\mathbf{EPU_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | 1.47 | (0.89) | -0.16 | (-1.05) | -0.12 | (-0.63) |
| Mania | 0.27 | (0.32) | 0.02 | (0.14) | -0.08 | (-0.41) |
| Anxiety | 0.37 | (0.39) | 0.50 | (3.65) | -0.10 | (-0.57) |
| Panic | 0.84 | (1.70) | 0.80 | (7.29) | -0.11 | (-0.75) |
| Revulsion/Blame | -0.71 | (-1.27) | 0.45 | (3.50) | 0.14 | (0.88) |
| Denial | 0.59 | (0.69) | 0.37 | (2.68) | -0.08 | (-0.46) |
| Guilt | 0.94 | (1.75) | 0.40 | (2.80) | -0.30 | (-1.65) |

*Notes:* Dummy variable $D_t$ takes a value of 0 during the internet bubble period (Oct-98 to Sep-02), and 1 during the Global Financial Crisis period (GFC) (Jan-06 to June 11). In the case of dot.com mania, $Return_t$ is the return on the Dow Jones Internet Index (DJII) during month t, $StDev_t$ is the standard deviation of daily returns on the DJII during month t, and $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII in month t. For the Global Financial Crisis period, $Return_t$ is the return on the S&P 500 Composite index during month t, $StDev_t$, is the value of the CBOE volatility index at the end of month t, and $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t. Emotions are measured at the end of each month, and are standardized using equation (1). $EPU_t$ is the news-based Economic Policy Uncertainty Index value obtained from www.policyuncertainty.com (based on Baker et al., 2016). All variables are normalized by dividing month t values by the standard deviation calculated over their respective period (internet bubble or GFC). Numbers in parentheses are the t-statistics. Intercepts and coefficients on control variables are not reported for brevity.

# 1 For Online Publication

## APPENDIX A: EMOTION DICTIONARY KEYWORD LISTS

### 1. Excitement

Appetite, Appetizer, Appetizing, Awesome, Awesomeness, Boost, Boosted, Booster, Boosting, Boosts, Brilliance, Brilliant, Brilliantly, Bull, Bullish, Bulls, Celebrate, Celebrated, Celebrating, Celebration, Celebrity, Climb, Climbed, Climber, Climbing, Climbs, Comfort, Comfortable, Comforting, Confidence, Confident, Confidently, Curiosity, Curious, Delight, Delighted, Delightful, Desirable, Desirability, Desire, Desired, Desires, Desiring, Double, Doubled, Doubles, Doubling, Eager, Eagerly, Eagerness, Enthuse, Enthusiasm, Enthusiast, Enthusiastic, Enthusiastically, Excite, Excited, Excitement, Excites, Expand, Expanded, Expanding, Expands, Expansion, Fantastic, Fantastically, Ferocious, Ferociously, Flourish, Flourished, Flourishes, Flourishing, Gamble, Gambles, Gambling, Glorious, Glory, Happiness, Happy, Jump, Jumped, Jumping, Jumps, New high, New low, Optimism, Optimist, Optimistic, Optimistically, Popular, Popularity, Popularize, Popularly, Pride, Proud, Ramp up, Reliability, Reliable, Rise, Risen, Rises, Run up, Run-up, Satisfaction, Satisfied, Satisfy, Sensation, Sensational, Sensationally, Sexy, Shoot, Shooter, Shooting, Shoots, Shot, Speculate, Speculated, Speculates, Speculating, Speculation, Speculations, Steal, Stealing, Steals, Stole, Stolen, Success, Successful, Successfully, Superior, Superiority, Surprise, Surprised, Surprises, Surprising, Surprisingly, Triple, Tripled, Triplet, Unprecedented, Winner

### 2. Mania

Amaze, Amazed, Amazement, Amazes, Amazing, Amazingly, Astonish, Astonished, Astonishes, Astonishing, Astonishment, Balloon, Balloons, Bandwagon, Boom, Boomed, Booming, Booms, Bubble, Bubbling, Bubbly, Crazy, Cried, Cries, Delusion, Delusions, Ecstatic, Enormous, Enormously, Euphoria, Euphoric, Exotic, Explode, Exploded, Explodes, Exploding, Explosion, Explosive, Exuberance, Exuberant, Exuberantly, Fantasy, Fever, Feverish, Feverishly, Frantic, Frantically, Frenzied, Frenziedly, Frenzy, Furious, Giant, Gigantic, Gigantically, Gold rush, Huge, Hype, Hyped, Hyper, Hypes, Hyping, Hysteria, Hysterical, Illusion, Illusions, Incredible, Incredibly, Infatuation, Love, Loving, Lunacy, Lunatic, Magic, Magical, Mania, Maniac, Maniacal, Manic, Obsessed, Obsession, Obsessional, Obsessive, Obsessively, Obsessiveness, Overwhelm, Overwhelmed, Overwhelming, Overwhelmingly, Passion, Passionate, Phenomena, Phenomenal, Phenomenally, Phenomenon, Rage, Rages, Revolution, Revolutionary, Revolutionize, Revolutionized, Rocket, Rocketed, Rocketing, Self-Delusion, Skyrocket, Skyrocket, Skyrocketed, Skyrocketing, Stratosphere, Stratospheric, Triumph, Triumphant, Vast, Vastly, Wave, Waves, Zeal

### 3. Anxiety

Afraid, Anxiety, Anxious, Anxiously, Anxiousness, Avoid, Avoidance, Avoided, Avoiding, Avoids, Bear, Bearish, Bears, Calm, Caution, Cautionary, Cautioned, Cautioning, Cautions, Cautious, Confuse, Confused, Confuses, Confusing, Confusingly, Confusion, Cool, Cooled, Cooler, Cooling, Cooling off, Cooling-off, Cools, Cools off, Danger, Dangerous, Dangerously, Dangers, Dangers, Dead, Deadly, Death, Deathly, Depress, Depressed, Depressing, Depression, Die, Dies, Difficult, Difficulties, Difficultly, Dislike, Dislikes, Distress, Distressed, Distressing, Downfall, Dying, Endangers, Endangers, Excess, Excesses, Excessive, Excessively, Fall, Fallen, Falls, Falter, Faltered, Faltering, Falters, Fear, Feared, Fearful, Fearing, Fears, Fearsome, Flameout, Flame-out, Fright, Frighten, Frightened, Frighteningly, Frightens, Hazard, Hazardous, Jitter, Jitters, Jittery, Liable, Nerve, Nerves, Nerviness, Nervous, Nervously, Nervousness, Nervy, Overheated, Overhyped, Over-hyped, Pessimism, Pessimist, Pessimistic, Pessimistically, Pressure, Pressured, Pressures, Pressuring, Reluctance, Reluctant, Risk, Risked, Riskier, Riskiness, Risks, Risky, Scare, Scared, Scares, Scaring, Scary, Shake out, Shakeout, Shake-out, Shrink, Shrinkage, Shrinking, Shrinks, Stress, Stressed, Stresses, Stressful, Stressing, Struggle, Struggled, Struggles, Struggling, Threat, Threaten, Threatened, Threatening, Threatens, Tumble, Tumbled, Tumbles, Tumbling, Uncertain, Uncertainly, Uncertainty, Uncomfortable, Uncomfortably, Unease, Uneasily, Uneasiness, Uneasy, Unreliability, Unreliable, Volatile, Volatility, Vulnerability, Vulnerable, Wonderful, Wonderfully, Wondrous, Worried, Worries, Worry, Worrying

### 4. Panic

Bewildered, Bomb, Bombed, Bombing, Bombing, Bombs, Burst, Bursted, Bursting, Bursts, Chaos, Chaotic, Chaotically, Collapse, Collapsed, Collapses, Collapsing, Contagion, Contagious, Crash, Crashed, Crashes, Crashing, Crater, Craters, Craze, Crazed, Crazily, Craziness, Crisis, Crush, Crushed, Crushing, Dark, Darken, Darkest, Darkness, Desperate, Desperately, Disaster, Disastrous, Disastrously, Doom, Doomed, Dooming, Dooms, Drama, Dramatic, Dramatically, Drop, Dropped, Dropping, Drops, Earthquake, Free fall, Free-fall, Gloom, Gloomy, Hurricane, Implode, Implodes, Imploding, Implosion, Liquidate, Liquidated, Liquidates, Liquidating, Liquidation, Meltdown, Nightmare, Nightmarish, Out of control, Panic, Panicked, Panicking, Panicky, Panics, Paranoia, Paranoid, Plummet, Plummeted, Plummeting, Plummets, Plunge, Plunged, Plunges, Plunging, Shock, Shocked, Shocker, Shocking, Shocks, Slump, Slumped, Slumping, Slumps, Terrifying, Trouble, Troubled, Troublesome, Troubling, Turmoil

### 5. Revulsion/ Blame

Absurd, Absurdity, Absurdly, Accusation, Accuse, Accused, Accusing, Anger, Angrily, Angry, Apathy, Awful, Awfully, Bankrupt, Bankruptcies, Bankruptcy, Bankrupted, Blame, Blamed, Blameless, Blames, Blaming, Bore, Bored, Boredom, Boring, Condemn, Condemnation, Condemned, Condemns, Contempt, Crime, Criminal, Crises, Critic, Critical, Critically, Criticise, Criticism, Criticize, Criticized, Criticizes, Criticizing, Despair, Destroy, Destroyed, Destroying, Destroys, Destruction, Disappoint, Disappointed, Disappointing, Disappointment, Disappoints, Disillusion, Disillusioned, Disillusioning, Disillusionment, Egregious, Egregiously, Envy, Error, Errors, Fail, Failed, Failing, Fails, Failure, Fault, Faulty, Fraud, Fraudful, Fraudulent, Frustrate, Frustrated, Frustrates, Frustrating, Frustration, Greed, Greediness, Greedy, Horrible, Horribly, Horrific, Horrify, Horror, Hurt, Hurtful, Hurting, Hurts, Insolvency, Insolvent, Ludicrous, Ludicrously, Miserable, Miserably, Misery, Mislead, Misleading, Misleads, Misled, Mistake, Mistaken, Mistakenly, Mistakes, Pain, Pained, Painful, Painfully, Painless, Perverse, Perversely, Perverseness, Perversion, Perversity, Perverted, Punish, Punished, Punishing, Punishment, Recession, Recessionary, Recessions, Resentment, Responsibility, Responsible, Ridicule, Ridiculous, Ridiculously, Sad, Sadly, Scandal, Scandals, Scorn, Scorned, Scorning, Scorns, Suffer, Suffered, Suffering, Suffers, Taint, Tainted, Terrible, Terribly, Tragedy, Tragic, Uglier, Ugliest, Ugliness, Ugly, Upset, Upsets, Upsetting, Woe, Woeful, Woefully, Woefulness, Woes, Wrong, Wrongs

## 6. Denial

Annoy, Annoyance, Annoyed, Annoying, Annoyingly, Arrogance, Arrogant, Arrogantly, Contradict, Contradicted, Contradicting, Contradiction, Contradictions, Contradicts, Contradictory, Defence, Defenceless, Defend, Defended, Defending, Defends, Defense, Defenseless, Defensive, Defensively, Defiance, Defied, Defies, Defy, Denial, Denied, Denies, Deny, Disagree, Disagreed, Disagreeing, Disagreeing, Disagreement, Disagrees, Disbelief, Disbeliefs, Disbelieved, Disbelieving, Hope, Hoped, Hopeful, Hopefully, Hopes, Hoping, Hubris, Hubristic, Ignorance, Ignorant, Ignore, Ignored, Ignores, Ignoring, Impatience, Impatient, Overconfidence, Overconfident, Refusal, Refuse, Refused, Refuses, Refusing, Reject, Rejected, Rejecting, Rejection, Rejects, Resist, Resistance, Resistant, Resisted, Resisting, Resists, Shrug, Shrug off, Shrugging, Shrugs, Shrunken, Storm, Stormy, Unstoppable, Victim, Victimized, Victims, Warn, Warned, Warning, Warns

## 7. Guilt

Apologize, Apologized, Ashamed, Burn, Burned, Burner, Burning, Burns, Burnt, Confess, Confessed, Confesses, Confessing, Confession, Confessor, Cry, Cry out, Crying, Damage, Damaged, Damages, Damaging, Discomfort, Discomforted, Discomforting, Discomforts, Dismay, Dismayed, Embarrass, Embarrassed, Embarrassing, Embarrassment, Excuse, Excused, Excuses, Grief, Grieve, Guilt, Guilty, Regret, Regrets, Regrettably, Remorse, Resenting, Shame, Shameful, Shamefully, Sorry

# 2 For Online Publication

## APPENDIX B: TABLES WITH UNCERTAINTY MEASURES OF JURADO ET AL. (2015) FOR THE REVIEWERS ONLY

**Table B.4: Contemporaneous regressions: Emotions, market returns, and uncertainty**

| | Excitement | Mania | Anxiety | Panic | Revulsion/Blame | Denial | Guilt |
|---|---|---|---|---|---|---|---|
| **Panel A: The internet bubble period (Oct-98 to Sep-02)** | | | | | | | |
| EPU | -2.02 | -0.19 | 4.12 | 8.33 | 3.56 | -0.79 | 26.48 |
| | (-1.32) | (-0.11) | (4.40) | (8.18) | (3.38) | (2.90) | (3.27) |
| FU | -0.06 | 0.13 | 0.48 | 0.34 | 0.16 | 0.80 | 3.70 |
| | (-0.28) | (0.51) | (3.24) | (1.47) | (0.95) | (1.67) | (3.09) |
| MU | -0.56 | -0.57 | 0.19 | 0.39 | 0.18 | 0.90 | 2.54 |
| | (-3.51) | (-3.21) | (1.47) | (2.22) | (1.32) | (2.43) | (2.62) |
| RU | -0.26 | -0.30 | 0.15 | 0.19 | 0.05 | 0.55 | 1.40 |
| | (-2.95) | (-3.16) | (2.27) | (1.95) | (0.66) | (2.85) | (2.70) |
| **Panel B: The Global Financial Crisis period (Jan-06 to Jun-11)** | | | | | | | |
| EPU | -0.45 | -0.36 | 0.50 | 1.29 | 2.44 | 3.35 | 2.20 |
| | (-1.81) | (-0.35) | (2.92) | (5.37) | (5.15) | (2.46) | (0.48) |
| FU | -0.24 | -0.36 | 0.34 | 0.72 | 1.62 | 3.06 | -1.70 |
| | (-1.72) | (-0.62) | (3.56) | (5.31) | (6.60) | (4.32) | (-0.66) |
| MU | -0.12 | 0.02 | 0.13 | 0.24 | 0.72 | 1.89 | 0.25 |
| | (-1.78) | (0.07) | (2.65) | (3.13) | (5.59) | (5.92) | (0.20) |
| RU | -0.06 | 0.05 | 0.05 | 0.14 | 0.35 | 0.90 | 0.26 |
| | (-1.61) | (0.34) | (2.10) | (3.62) | (5.04) | (5.17) | (0.39) |

*Notes:* The table reports the results of OLS regressions models (2) and (3). $Return_t$ is the return on the Dow Jones Internet Index (DJII) during month t in panel A and return on the S&P 500 Composite index during month t in panel B. Emotions are measured at the end of each month, and are standardized using equation (1). $EPU_t$ is the news-based Economic Policy Uncertainty Index value obtained from www.policyuncertainty.com (based on Baker et al., 2016). $FU_t$ is the one-month ahead financial uncertainty, $MU_t$ is the one-month ahead macro uncertainty, and $RU_t$ is the one-month ahead real uncertainty obtained from www.sydneyludvigson.com (based on Jurado, et al., 2013). Numbers in parentheses are the p-values. Intercepts and coefficients on control variables are not reported for brevity.

**Table B.5: Mean emotions and uncertainty measures during the extreme market events and associated control periods**

| | Internet bubble period | | | | Global Financial Crisis period | | | |
|---|---|---|---|---|---|---|---|---|
| | Bubble period | Control period | Difference in means | t | GFC period | Control period | Difference in means | t |
| **B. Uncertainty** | | | | | | | | |
| $StDev_t$ | 0.698 | 0.243 | 0.455 | (12.05) | 22.915 | 14.119 | 8.797 | (6.77) |
| $Volume_t$ | 0.674 | 0.303 | 0.371 | (12.38) | 1.990 | 1.079 | 0.910 | (13.48) |
| $EPU_t$ | 1.126 | 0.957 | 0.169 | (2.68) | 112.659 | 81.203 | 31.456 | (5.66) |
| $FU_t$ | 1.104 | 0.726 | 0.378 | (40.13) | 0.979 | 0.765 | 0.214 | (6.92) |
| $MU_t$ | 0.668 | 0.611 | 0.058 | (7.74) | 0.750 | 0.655 | 0.095 | (6.07) |
| $RU_t$ | 0.615 | 0.599 | 0.016 | (4.08) | 0.669 | 0.623 | 0.046 | (5.77) |

*Notes:* The internet bubble period is from Oct-1998 to Sep-2002 with Jan-1995 to Apr-1995 and Sep-2004 to Dec-2004 as its control period. The Global Financial Crisis (GFC) period is from Jan-2006 to Jun-2011 with Jan-2004 to Dec-2005 as its control period. Emotions are measured at the end of each month, and are standardized using equation (1). $StDev_t$, is the standard deviation of daily returns on the Dow Jones Internet Index (DJII) during month t for the internet bubble period, and the value of the VIX index at the end of month t for the GFC period. $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII over month t for the internet bubble period, and the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t for the GFC period. $EPU_t$ is the news-based Economic Policy Uncertainty Index value at the end of month t obtained from www.policyuncertainty.com (based on Baker et al., 2016). $FU_t$ is the one-month ahead financial uncertainty, $MU_t$ is the one-month ahead macro uncertainty, and $RU_t$ is the one-month ahead real uncertainty obtained from www.sydneyludvigson.com (based on Jurado, et al., 2013). The table presents the t-statistics for test of difference in means. Since the data for the Dow Jones Internet Index is only available from July-1997, the control period for StDev and Volume is from Sep-2004 to Dec-2004. For ease of exposition Volume are multiplied by 100.

**Table B.6: Tests of differences in mean emotions and uncertainty in the up and down phases of our crisis periods**

| | **Internet bubble period** | | | | **Global Financial Crisis period** | | | |
|---|---|---|---|---|---|---|---|---|
| | Up phase | Down phase | Difference in means | t | Up phase | Down phase | Difference in means | t |
| **B. Uncertainty** | | | | | | | | |
| $StDev_t$ | 0.704 | 0.694 | 0.010 | (0.12) | 19.856 | 29.953 | -10.097 | (-3.96) |
| $Volume_t$ | 0.825 | 0.591 | 0.234 | (4.39) | 1.843 | 2.329 | -0.486 | (-3.60) |
| $EPU_t$ | 0.876 | 1.263 | -0.387 | (-3.22) | 104.710 | 130.942 | -0.262 | (-2.23) |
| $FU_t$ | 1.063 | 1.127 | -0.063 | (-3.60) | 0.911 | 1.134 | -0.223 | (-3.60) |
| $MU_t$ | 0.619 | 0.695 | -0.077 | (-7.00) | 0.708 | 0.847 | -0.139 | (-4.73) |
| $RU_t$ | 0.589 | 0.629 | -0.040 | (-6.73) | 0.656 | 0.701 | -0.046 | (-2.74) |

*Notes:* The period from Oct-1998 to February-2000 is the up phase of the internet bubble period, and from Mar-2000 to Sep-2002 its down phase. For the Global Financial Crisis (GFC), Jan-06 to Jun-07 and Mar-09 to Jun-11 are the up phases, while Jul-07 to Feb-09 is the down phase. $StDev_t$ is the standard deviation of daily returns on the Dow Jones Internet Index (DJII) during month t for the internet bubble period, and the value of the VIX index at the end of month t for the GFC period. $Volume_t$ is the average of the daily total value of shares traded divided by end of day market capitalization of the DJII over month t for the internet bubble period, and the average of the daily total value of shares traded divided by end of day market capitalization of the S&P 500 Composite index over month t for the GFC period. $EPU_t$ is the news-based Economic Policy Uncertainty Index value at the end of month t obtained from www.policyuncertainty.com (based on Baker et al., 2016). $FU_t$ is the one-month ahead financial uncertainty, $MU_t$ is the one-month ahead macro uncertainty, and $RU_t$ is the one-month ahead real uncertainty obtained from www.sydneyludvigson.com (based on Jurado, et al., 2013). The table presents the t-statistics for the two-sample test of difference in means. For ease of exposition Volume is multiplied by 100.

**Table B.7: Relationship between emotions and market behavior in the two crisis periods**

| | $\beta_1$ | t | $\beta_2$ | t | $\beta_3$ | t |
|---|---|---|---|---|---|---|
| **Panel A.** $\mathbf{EPU_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | 1.47 | (0.89) | -0.16 | (-1.05) | -0.12 | (-0.63) |
| Mania | 0.27 | (0.32) | 0.02 | (0.14) | -0.08 | (-0.41) |
| Anxiety | 0.37 | (0.39) | 0.50 | (3.65) | -0.10 | (-0.57) |
| Panic | 0.84 | (1.70) | 0.80 | (7.29) | -0.11 | (-0.75) |
| Revulsion/Blame | -0.71 | (-1.27) | 0.45 | (3.50) | 0.14 | (0.88) |
| Denial | 0.59 | (0.69) | 0.37 | (2.68) | -0.08 | (-0.46) |
| Guilt | 0.94 | (1.75) | 0.40 | (2.80) | -0.30 | (-1.65) |
| **Panel B.** $\mathbf{FU_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | -11.21 | (-6.77) | -0.05 | (-0.37) | -0.17 | (-0.89) |
| Mania | -12.35 | (-15.14) | 0.08 | (0.54) | -0.16 | (-0.83) |
| Anxiety | -13.07 | (-13.75) | 0.45 | (3.25) | -0.01 | (-0.04) |
| Panic | -13.73 | (-22.95) | 0.27 | (2.00) | 0.32 | (1.83) |
| Revulsion/Blame | -14.66 | (-26.21) | 0.18 | (1.38) | 0.46 | (2.82) |
| Denial | -13.78 | (-16.47) | 0.23 | (1.75) | 0.23 | (1.33) |
| Guilt | -11.66 | (-21.97) | 0.39 | (2.80) | -0.45 | (-2.52) |
| **Panel C.** $\mathbf{MU_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | -7.75 | (-4.94) | -0.44 | (-3.14) | 0.17 | (0.97) |
| Mania | -8.67 | (-11.08) | -0.40 | (-2.87) | 0.39 | (2.18) |
| Anxiety | -7.81 | (-7.84) | 0.20 | (1.42) | 0.13 | (0.73) |
| Panic | -7.04 | (-11.48) | 0.33 | (2.44) | 0.09 | (0.51) |
| Revulsion/Blame | -8.37 | (-14.80) | 0.21 | (1.63) | 0.37 | (2.24) |
| Denial | -7.79 | (-9.96) | 0.32 | (2.59) | 0.25 | (1.52) |
| Guilt | -6.11 | (-11.49) | 0.33 | (2.36) | -0.29 | (-1.58) |
| **Panel D.** $\mathbf{RU_t = \beta_0 + \beta_1 D_t + \beta_2 Emotion_t + \beta_3 (Emotion * D)_t + \beta_4 Return_t + \varepsilon_t}$ | | | | | | |
| Excitement | -12.53 | (-7.81) | -0.39 | (-2.68) | 0.14 | (0.78) |
| Mania | -13.77 | (-17.46) | -0.40 | (-2.83) | 0.42 | (2.33) |
| Anxiety | -11.96 | (-11.91) | 0.31 | (2.10) | -0.02 | (-0.10) |
| Panic | -12.23 | (-19.90) | 0.31 | (2.24) | 0.16 | (0.90) |
| Revulsion/Blame | -13.49 | (-23.12) | 0.12 | (0.89) | 0.42 | (2.47) |
| Denial | -12.31 | (-15.45) | 0.37 | (2.95) | 0.15 | (0.92) |
| Guilt | -11.08 | (-20.73) | 0.35 | (2.45) | -0.28 | (-1.52) |

*Notes:* $D_t$ is the dummy variable that takes a value of 0 during the internet bubble period (Oct-98 to Sep-02) and 1 during the Global Financial Crisis period (GFC) (Jan-06 to June 11). In the case of dot.com mania, $Return_t$ is the return on the Dow Jones Internet Index (DJII) during month t, and $StDev_t$, is the standard deviation of daily returns on the DJII during month t. For the Global Financial Crisis period (GFC), $Return_t$ is the return on the S&P 500 Composite index during month t, $StDev_t$, is the value of the CBOE volatility index at the end of month t. Emotions are measured at the end of each month, and are standardized using equation (1). $EPU_t$ is the news-based Economic Policy Uncertainty Index value obtained from www.policyuncertainty.com (based on Baker et al., 2016). $FU_t$ is the one-month ahead financial uncertainty, $MU_t$ is the one-month ahead macro uncertainty, and $RU_t$ is the one-month ahead real uncertainty obtained from www.sydneyludvigson.com (based on Jurado, et al., 2013). All variables are normalized by dividing month t values by the standard deviation calculated over their respective period (internet bubble or GFC). Numbers in parentheses are the t-statistics. Intercepts and coefficients on control variables are not reported for brevity.