

Asset Pricing Bubbles and Investor Emotions: An Empirical Analysis of the 2014
– 2016 Chinese Stock Market Bubble

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Abstract

Conventional economic and financial models find difficulty in explaining asset pricing bubbles in a way that is compatible with the underlying investor social and emotional processes at work. In this paper we explore the nature of the powerful emotions investors are held sway by as prices shoot up and then collapse using formal content analysis of media reports and original domain-specific constructed emotion category word dictionaries. In particular, we show how emotions such as excitement and anxiety, mania and panic are associated with, and potentially help drive, speculative bubbles. We apply our model to the very recent Chinese stock market bubble and show empirically how different investor emotional states are an important factor in helping explain the dramatic movements in the Chinese market. The paper also conducts vector autoregressive (VAR) analysis Granger causality tests and demonstrates the ability of investor emotions to predict subsequent market returns during, and the bursting of, the 2014-2016 Chinese stock market bubble.

1. Introduction

Extant financial and economic theories find great difficulty in explaining asset pricing bubbles within the context of traditional economic models (for summaries of attempts see e.g., the surveys of Brunnermeier and Oehnike, 2013; Scherbina, 2013; Jarrow, 2015). Even the definition of a bubble is contentious and there is a continuing debate as to whether they actually exist, and are they “rational” or “irrational” (O’Hara, 2008). Conventional models of bubbles are usually theoretical and of a mathematical nature and variously revolve around ideas of herding, informational cascades and the “greater fool” theory (see Hirshleifer and Teoh, 2003 for an accessible overview). The part played by investor emotions and social and group processes in bubbles is effectively ignored (e.g., Shiller, 2014; Hirshleifer, 2015). In fact, as Hirshleifer (2015, p. 151) argues, were this to be formally acknowledged it would “offer a deeper basis for understanding the causes and consequences of financial bubbles and crises”.

Possibly because of what is arguably the limited success of conventional models of asset pricing bubbles many economists and finance academics make strenuous efforts to deny

asset pricing bubbles exist; if markets are efficient and investors are rational such bubbles should not occur. Eugene Fama (2014), for example, even used his 2013 Swedish National Bank (Nobel Memorial) Prize in Economic Sciences address to argue against the existence of asset pricing bubbles and thus that market efficiency is not violated. However, by considering, inter alia, the US market index, using a graph with a natural logarithmic scale so major price movements are visually attenuated, and focusing mainly on index values many years apart, rather than the actual bubble trajectory itself, his arguments are less than convincing. Fama's attack on the work of his co-2013 Laureate Robert Shiller, who in his parallel address (2014) questions the rationality of markets, also well illustrates the strong emotions aroused not just during bubbles but also in academic commentators. There is even a tendency among some economists to see bubbles as unavoidable implying trying to understand their causes makes little sense (Shulman, 2016), or alternatively to argue that bubbles are in fact "rational" and thus consistent with neo-classical economic theory (Engsted, 2016).

Accounts of what actually happens in financial crises and asset pricing bubbles (e.g., Mackay, 1995; Galbraith, 1993; Cassidy, 2002; Tuckett and Taffler, 2008; Aliber and Kindelberger, 2015; Taffler and Bellotti, 2015) 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 the emotional dynamics of market participants during asset pricing bubbles. To do this we use the lens of how the financial media contemporaneously reports on the path-dependent trajectory an asset pricing bubble represents as it moves through its different stages, as it starts out, inflates, booms, bursts, implodes and finally leads to increasingly stronger ripple effects in the surrounding economy.

Formal form-orientated content analysis is conducted employing appropriately derived key word dictionaries to measure the relative salience of the various emotions experienced by market participants in different stages of the bubble, and their interactions. Our analysis confirms how investors appear to be driven by deep-seated emotions in asset pricing bubbles and are caught up in the associated excitement in a powerful way denying the underlying risk in the departure from underlying reality. When the bubble bursts emotions go into reverse with the speculative asset now reviled and dumped as quickly as possible.

In particular in this paper we examine the recent Chinese stock market bubble of 2014 – 2016 when in a period of just under a year from July 1 2014 to June 12 2015, when the Shanghai Stock Exchange Composite Index (SSEI) peaked, the Chinese market went up by

no less than 150% (with the SSEI rising from 2050 to 5166). It then went into free fall collapsing by 40% over the following 3½ months to September 28 2015 (when the SSEI stood at 3083) despite strenuous attempts by the Chinese government to stem the rout, and after a small reversal over the following three months the SSEI fell further to represent an overall loss of value of almost 50% at its trough on 28 January 2016 (when the index stood at 2655). In a short period of less than 18 months from peak to trough the Chinese stock market lost \$5.6 trillion or more than half of China’s GNP. Figure 1 illustrates the SSECI trajectory from January 2014 to June 2016 with the different emotional states of the Chinese market overlaid. Interestingly, this bubble closely resembles, albeit on an attenuated time scale, the earlier Chinese share price bubble of 2005 to 2008 when between June 2005 and October 2007 the Chinese market rose five-fold and then fell by over 70% over the following year.

Figure 1 here

Our analysis shows how speculative bubbles are essentially highly emotional processes. Investors become caught up in wish fulfilling fantasies and are carried away by the excitement the “phantastic object” (Tuckett and Taffler, 2008) represented by the implicit promise of easy wealth implicitly promises with underlying investment fundamentals ignored till the bubble bursts and panic and loss ensue. Specifically, we demonstrate how it is possible to measure the underlying emotional states of investors (the market) in different stages of an asset pricing bubble and, as a result, potentially predict how it is likely to play out. In particular, we model the bubble process empirically using vector autoregression (VAR) and different investor emotions as predictor variables to forecast subsequent movements in the SSECI. Our results are consistent with investor fantasy and associated powerful emotions driving market prices during the 2014 – 2016 bubble and, importantly, the evidence for this direction of causality is far stronger than that for market prices driving investors’ states of mind and behaviour. Based on our empirical analysis, we conclude that there is a need both to go beyond traditional theoretical models in seeking to explain asset pricing bubbles and explore more formally the underlying emotional processes at work to be able to understand and manage these more effectively.

This paper proceeds as follows. In the next section we discuss our underlying theory and motivation and in the following one we establish our hypotheses. Section 4 then describes our content analysis emotion word dictionary construction, our data research corpus

and research method. Our empirical tests of our model follow in the results section. In section 6 we present our VAR model and show how investor emotions drove the 2014 – 2016 Chinese stock market bubble. Discussion of the implications of our findings and the associated conclusions we draw about the need to explore the underlying emotional processes at work in asset pricing bubbles to be able to understand and manage these more effectively are provided in our final section.

2. Theory and motivation

A common feature of the myriad of financial crises described in Aliber and Kindelberger (2015) ranging 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 a five stage path-dependent emotionally driven trajectory. In each case patchy excitement about an innovation leads to euphoria (or mania), denial (or manic defence) 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 psychological perspective and point out 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. They view asset pricing bubbles as due to a disturbance in the market's sense of reality brought about by an exciting new idea that captures the financial imagination (which they term a "phantastic object") with an associated move from individuals investing employing the "reality principle" towards judgments based essentially on the "pleasure principle". Collective wishful thinking becomes the order of the day. Mental conflict between what investors on one level "know" to be the underlying or intrinsic value of the asset and how the bubble asset is actually being priced in the market is defended against and avoided with anything that might challenge the very satisfying "fantasy" valuation evacuated from mental awareness. Together these processes allow the exciting phantastic object to be pursued as if it were "real" with any associated anxiety denied and repressed. However, eventually reality has to intrude, panic takes over and the phantastic object is now despised and those who are perceived to have promoted what turns out to have been only a very satisfying wish-fulfilling fantasy now a source of blame.

As the bubble rises to its peak market participants unconsciously collude in collective denial in a fight against underlying reality including recourse to the superficially plausible cover story that "this time it is different" (Aliber and Kindelberger, 2015, p. 41). Sceptical

commentators felt to be denying the value of the phantastic object, and spoiling the party are treated with contempt and dismissal (e.g., Cassidy, 2002). Their warnings are viewed as an attack motivated either by “deficient understanding or uncontrolled envy, on the wonderful process of enrichment ... [or] thought to demonstrate a lack of faith in the inherent wisdom of the market itself.” (Galbraith, 1993, p.2) Importantly, observation of actual bubbles demonstrates how when the bubble eventually bursts this is not due to new information but that the repressed anxieties can no longer be rendered unconscious. The whole process then goes into reverse with investors now taking flight in a headlong panic to rid themselves of the now despised phantastic object. Anger and blame of others rather than feelings of personal guilt erupt allowing investors to avoid the painful realisation 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 guilt when unconscious defences against reality no longer work.

Shiller (2015, chapter 10) postulates bubbles develop through word of mouth communication; investing ideas can spread like epidemics. In particular, Shiller (2014, p. 1487) defines a speculative bubble as:

“A situation in which news of price increases spurs investor enthusiasm which spreads by psychological contagion from person to person, in the process amplifying stories that might justify the price increases and bringing in a larger and larger class of investors, who, despite doubts about the real value of an investment, are drawn to it partly through envy of others’ successes and partly through a gambler’s excitement.”

The key components of this definition are epidemic spread, the emotions of investors, and the nature of the news and information media. Shiller argues that 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.” However, his definition does not mention anything about the bursting of the bubble and its subsequent collapse, which Aliber and Kindleberger (2015) stress are just as much an integral part of a bubble as its initial inflation. Nor does Shiller attempt to go into any of the underlying psychological processes at work in any detail either at individual investor or market level.

Recurrent asset pricing bubbles can be viewed on one level as the inevitable consequence of investors’ unconscious search for transformational phantastic objects.

Conventional attempts to explain such events are constrained by economists' assumptions about individuals' rational utility maximising behaviour or in the case of behavioural finance models, the operation of individual level cognitive processing errors. This paper suggests that explicitly recognising the inherently emotional nature of investor relationships with their assets, and their fantasies and unconscious needs, may well be helpful in understanding the nature and trajectory of asset pricing bubbles and how such damaging repetitive tendencies in financial markets might be alleviated.

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 they are acted out in their investment decisions in the way in which they report on what is going on in the market. Therefore, in this paper we utilise the Chinese financial media, its news reports, comments, opinions and press releases, as a lens through which to explore the different emotions of investors in the market as the dynamic of the bubble evolves through its different stages. To test whether stock market valuations during the recent Chinese stock market bubble were essentially driven by investor emotions and fantasies rather more than by rational analysis, we test our 5-stage path-dependent model of investor emotion against what was actually happening in the Chinese stock market from 2014 to 2016. Specifically, we conduct formal content analysis of Chinese media reports on the Chinese stock market employing seven different emotion word dictionaries to measure market sentiments and explore how these change and the interrelationships between them in different stages of the bubble.

In addition, we test formally whether being able to measure investor fantasies and emotions dynamically can help us predict prices in a stock market bubble directly. Specifically, we test our underlying theory of investor behaviour empirically by using a VAR model and Granger causality tests to investor emotions derived via content analysis of associated market media coverage and the market returns during the recent Chinese stock market bubble. Evidence consistent with investor emotions predicting subsequent market prices in this period rather than emotions being driven by market prices would support our main thesis about the key role investor fantasy plays in driving market bubbles.

3. Hypothesis construction

3.1 Five-stage path dependent emotional asset pricing bubble trajectory

Kindleberger and Aliber (2005, p.25) define an asset pricing bubble as “an upward price movement over an extended period of 15-40 months that then implodes”. That such bubbles or ‘manias’ constitute an essentially emotional process is highlighted by the language conventionally used to describe them (Taffler and Tuckett, 2008). Based on a general model of financial crises originating with Hyman Minsky, 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”.² However, a more formal reading of such bubbles would tend to distinguish both between euphoria and boom, and panic and revulsion because the former psychologically leads to the latter. As such, we work with a 5-phase model in our subsequent analysis though noting that although these phases are presented sequentially for exposition purposes, there is inevitably some overlap as the psychological drama of the bubble unfolds. The underlying research question is whether the nature of this emotionally-driven path-dependent trajectory we hypothesize can help explain why the recent Chinese stock market bubble, and how, and its rapid inflation and subsequent implosion as in the parallel case of the equally dramatic dot.com mania at the turn of the millenium (Tuckett and Taffler, 2008) and the equivalent Chinese bubble of the last decade (Taffler and Bellotti, 2015). Is this psychologically-informed model consistent with the way Chinese stocks were being treated and valued by investors between 2014 and 2016, and what were the consequences?

Representing Aliber and Kindleberger’s (2015) anatomy of an asset pricing bubble more formally we term the beginning phase of “displacement” or exogenous shock as “emerging to view”, when Chinese stocks began to be perceived as transformational phantastic objects in the minds of investors. Next, once these unconscious mental images are established in this way, we predict a headlong and compulsive craze among investors to acquire more of such assets at almost any price helped by observing how other investors have

² Or *Torschlusspanik* (door-shut panic) (p. 46) in German as investors crowd to get out before the door slams shut.

profited so well from their speculative activity, inter alia, assisted by the media. This we term the “rush to possess” phase.

Following these two stages we predict a crucial third stage with Chinese stock prices continuing to boom, and departing even further from fundamental value, despite increasing evidence that such stock valuations are clearly unrealistic and unsustainable. We argue, however, that normal investment criteria are no longer salient when applied to phantastic objects. This is due to the specific ways investors unconsciously collude to maintain their exciting idealized wish-fulfilling fantasy against the external challenges of material reality. This is the phase of “psychic defense”. Ultimately, however, such exciting fantasies are unsustainable, however pleasurable and emotionally satisfying; external reality cannot be held at bay forever. The emotional logic underpinning the extreme stock valuations is no longer maintainable and the stock market bubble implodes. Conscious awareness of having been caught up in what has turned out to be only an investment fantasy which was not real is now paramount, together with the pain of loss. This is felt both in terms of what the phantastic object represented emotionally, as well as the pain of having to give it up and the resulting financial loss. Investors now seek to liquidate their investments as fast as possible. This is the “panic” phase.

Fifth and finally, after the dramatic collapse in stock market valuations, we predict feelings of embarrassment, shame, guilt and loss will continue to predominate in markets. Investors will be wary of further involvement in the market that has let them down so badly, leading to potentially adverse consequences for rational asset pricing over quite a significant period of time subsequently. Those caught up in the bubble will look for other parties to blame for being caught up in the wish-fulfilling fantasy and the inevitable unwanted and very painful consequences that result. This we term the “revulsion and blame” phase.

Although clearly these five phases of a speculative bubble, emerging to view, rush to possess, psychic defense, panic and revulsion and blame will overlap to some degree, nonetheless our figures break the 2014 to 2016 Chinese bubble down into our five phases for illustrative purposes.

3.2 Hypotheses

Drawing on our seven content analysis key word dictionaries constructed to measure the following different investor emotions: excitement, anxiety, happiness, worry, mania, panic, and revulsion as motivated and described below, we set up the following hypotheses to test

our main thesis about the role of emotions in stock market bubbles using our Chinese stock market bubble data.

Our underlying proposition is that powerful investor emotions are an integral part of asset pricing bubbles. This leads to our first alternate hypothesis:

H1: Between 2014 and 2016, Chinese stock market returns and market emotional states are closely associated.

Shiller (2014) views stock market bubbles in the context of social epidemics with market price increases driving investor sentiment which then drives prices up further. We test this proposition explicitly in alternate hypothesis 2:

H2: Market returns are driving investor emotions between 2014 and 2016 in the Chinese stock market.

An alternative perspective we explore is that powerful investor emotions are driving asset prices in stock market bubbles which is what the path dependent trajectory of figure 1 might be illustrating. Our third alternate hypothesis directly follows:

H3: Investor emotions are driving market returns during the recent Chinese stock market bubble.

Finally, we posit that market bubbles generate very powerful emotions among the investors who first manifest an obsessive need to possess the phantastic object at all costs and then to dispose off it in an extreme state of revulsion as quickly as possible when the reality intrudes and the bubble bursts. We test this proposition in our alternate hypothesis 4:

H4: Powerful investor emotions dominate weak investor emotions during the 2014 to 2016 Chinese stock market bubble.

4. Dictionary construction, data and research process

4.1 Selection of emotion word categories

Investment decisions create strong emotions of both excitement (associated with the pleasurable idea or fantasy of actual or imagined future gains) and anxiety (over the potential pain of actual or potential future loss). These emotions and their dynamic inter-relationship can be empirically measured using appropriate content analysis techniques (e.g., Tuckett, Smith and Nyman, 2014); Kuhnen and Knutson (2011) describe some of the underlying neuropsychology. As such, in seeking to test the role investor emotions play as potential drivers of asset pricing bubbles, measuring the levels of Excitement and Anxiety in the market in different stages of a bubble is fundamental, hence our use of excitement and anxiety key word dictionaries. Construction of our Mania, Panic, and Revulsion key word dictionaries are also required to test our first three hypotheses. We finally establish Happiness and Worry word dictionaries which represent less powerful emotions or feelings to test H4 – do such weaker emotions impact market pricing during the 2014 – 2016 Chinese stock market bubble in the same way as we hypothesise our five categories of strong emotions do?

4.2 Construction of key word emotion dictionaries

Henry and Leone (2016) show that domain specific wordlists in content analysis perform better than general wordlists and also equal weighting of words is just as successful as more complex weighting procedures. Since there are no existing emotion word dictionaries in Chinese to the knowledge of the authors, and certainly none relevant to analyzing the Chinese financial media, we needed to build domain specific ones ourselves. To do this we divided our 30 month bubble period into 10 quarters and in each quarter ranked publications by article frequency. News stories and articles published in the five top sources were then downloaded and physically inspected for content appropriate for our emotion word dictionary construction purposes. Of those articles meeting our dictionary construction needs the number retained for detailed analysis from each source in each quarter depended on their length. In total, we ended up with 532 news articles with clear emotional content spread across 16 different journals. All articles were then carefully read and all words with an emotional component tabulated; around 1,000 separate words in total. These were then

categorized into our seven different emotion categories (Mania, Excitement, Happy, Worry, Anxiety, Panic, and Revulsion) by two researchers independently with the small number of classification disagreements resolved by discussion. However, the volume of words in a number of our emotion categories was too great for ready application in the main stage of our research which involved analysis of our full article corpus (see below) so words appearing with very low frequency in it were removed leaving 439 in total across our seven key word emotion categories. Appendix 1 provides our key word dictionary by emotion word category in Chinese together with English translation and the associated word frequency cut off criteria for inclusion.³ Subsequently, an additional two word categories were added: “Bubble” and “Government Intervention” to address the level of awareness of the existence of the asset pricing bubble at its different stages and to reflect action by the Chinese government in an attempt to stabilise the market after the bubble had burst. Bubble classification key words (8 in number) were taken from the “Panic” emotion word dictionary and those in the Government Intervention one (7 in number) from the “Happy” emotion word dictionary.

4.3 Research corpus

All the media reports we analyse are published in Chinese and as such are directly accessible to Chinese investors; they are all downloaded from the Factiva database. To arrive at the corpus of news stories and articles we work with for our 30 month period 1/1/2014-6/30/2016 on a month by month basis. We first search systematically in Factiva each month using the following search conditions:

Searching key words: (all in Chinese) *Chinese stock/share market OR Chinese stock/share OR stock/share market OR stock/share*

Region: *China; Beijing; Shanghai; Shenzhen etc.*

Language: *Simplified Chinese*

Sort by: *Relevance*

Subject: *Equity markets*

³ This is available from the first author.

However, the resulting high volume of articles identified included a large proportion which simply reported firm results, were public company notices or mentioned the formation of new investment funds and thus not relevant for our purposes. As such, all news reports downloaded in the initial screening process had to be checked for appropriateness by looking at their headlines and if these were not clear enough, by inspection of the actual article content to guarantee their relevance. Our target was to work with three hundred news articles each month. If the total number of the relevant articles for a specific month was less than three hundred, all were chosen to work with; if the number of available articles exceeded three hundred, the three hundred were chosen spread equally by date across the whole month.

In total, we ended up working with a corpus of around 6,700 suitable news stories and articles, an average of around 225 a month. Our ten principal media sources accounting for in total almost 2/3 of the articles we worked with (63.5%) with the Dow Jones Newswires and The Wall Street Journal (Chinese Edition) together accounting for almost 3 out of 10. Since all downloadable media news and articles published in China in Chinese are censored by the Chinese government, there is unlikely to be any particular bias in the way we constructed our research database.

4.4 Data analysis and standardisation

Wordscount,⁴ a Chinese software package, is used to count the frequency of occurrence of words in each of our seven emotion key word dictionaries and two additional categories in our 6,700 article research corpus broken down by each of the 30 months in our data period. There are many benefits in using this software. First, it can count the frequency of words in both the Chinese and English languages.⁵ Secondly, it can count not only single words such as “amazing” but also word combinations such as “government support”. Finally, the frequency of each word in each category in any period can be ranked from top to the bottom or vice versa making our empirical analysis more straightforward.

As there are different volumes of articles in our research corpus each month and these will be of different length the total frequency of emotion words in a particular category in a

⁴ Available at <http://www.yuneach.com/soft/WordsCount.asp>.

⁵ We replicate this analysis using Western media sources and parallel English key word emotion dictionaries although our results are broadly similar and thus not reported here. *Inter alia*, we would expect that because Western financial journalists are not directly caught up in the stock market bubble in the same way as Chinese financial journalists would be, emotional engagement would be less charged and this is what we find in our content analysis and empirical results with results a little attenuated in comparison.

month cannot be compared with that for the same category in other months directly due to the differing total number of words. However, comparison can be realized through the following relationship:

$$\text{Key word dictionary category monthly frequency standardization} = \frac{\text{total frequency of emotion words in the respective category in the month}}{\text{total amount of words in all the news and articles downloaded in that month}} \quad (1)$$

All frequencies used in this paper are standardized in this way.

4.5 SSECI index vs standardized emotion category word frequency

To test our five-step emotional trajectory asset pricing bubble theory we need to explore the relationship between the relative salience of our different investor emotions as reflected in media reports as the Chinese stock market bubble evolves, bursts and deflates as measured by movements in the Shanghai Stock Exchange Composite Index between 2014 and 2016. We do this by overlaying the monthly standardized frequency of words in the respective emotion category plotted in bar chart form on the daily value of SSECI index so the dynamic relationship between the market index and investor emotions can be tracked through each phase of the bubble.

5. Descriptive results

In this paper we explore the extent to which investor emotions and fantasies are a prime driver of asset pricing bubbles. This section presents our empirical results. In the first sub-section below we conduct an initial analysis to examine our underlying thesis before testing our formal hypotheses in subsequent sub-sections.

5.1 Overview

As outlined in section 3.1 above our psychological bubble model is built around the idea of how the continuing search by investors for 'transformational' phantastic objects can help explain the morphology of asset pricing bubbles as they unfold. Investors become increasingly aroused and stimulated as the bubble inflates and the phantastic object appears to be 'real' and this is then followed by their anger and despair when the bubble bursts and the phantastic object turns out to be 'worthless'.

To explore our general proposition that investors' emotional states both serve to drive and reflect the different stages of an asset pricing bubble, and the way in which they experience associated market movements, figure 2 overlays monthly standard deviation during our 30 month period on the SSECI which highlights the high state of market excitement during this period. The tension between investor excitement and anxiety, and mania and panic which continuously contend in asset pricing bubbles and the resulting levels of uncertainty is reflected in stock market volatility. Figure 2 shows that although the two series are highly correlated ($r=0.83$) volatility rises much more dramatically from the start of the bubble to its peak and again increases significantly at different stages as the bubble implodes. For example when the SSECI peaks in June 2015 it is standing at 2.5x its value a year earlier whereas the equivalent ratio for monthly standard deviation is no less 7.5x with continuing high levels of volatility maintaining through to the early part of 2016.

Figure 2 here

The highly excited market state during this short period is equally illustrated in figure 3 which reports trading volumes as a ratio of average monthly market turnover in the pre-bubble period of January to June 2014. As the SSECI shoots up to its peak, trading volume goes up by no less than 14X, again consistent with manic investor behaviour and then panic and revulsion as reflected in the dramatic collapse in trading activity.

Figure 3 here

To explore our general proposition, figure 4 plots our main composite variable which combines monthly levels of excitement and anxiety ($(\text{Excitement} - \text{Anxiety})/(\text{Excitement} + \text{Anxiety})$) against the SSECI monthly returns between January 2014 and June 2016. As can be seen both the variables are very volatile and highly correlated ($r = 0.77$). This picture is confirmed in the individual correlations between emotions and market returns in the correlation matrix of table 1. As can be seen, the positive emotions (mania, excitement, and happy) are all positively correlated to the concurrent month returns ($r = 0.43, 0.75, \text{ and } 0.41$ respectively), as well as to each other. The negative emotions (worry, anxiety, panic, and revulsion), all have strong negative correlations with contemporaneous returns, strong

positive correlations with each other, and are also negatively correlated with positive emotions.

Figure 4 and Table 1 here

Figure 5 plots the level of the SSECI against mention of the word “bubble” during this period. It shows that there is an increasing awareness of the fragile bubble state in the market as the standardized frequency of bubble mentions as index peaks stands at five times its level in the pre-bubble period. Simultaneously, the Chinese government tried to stem the tide as demonstrated by the frequency of mentions of government intervention in figure 6 in the Chinese media. These attempts included the suspension of more than half of the country’s stocks, reducing interest rates, relaxing stock market regulations, stopping new issues and requiring the 21 Chinese securities houses not to sell any stocks if the SSECI fell below 4500. In addition, a \$250 billion investment fund known as the National Team was set up to buy stocks in the SSECI in an attempt to buoy up the index. However, not surprisingly, all these actions proved to be of no avail in the face of investor panic; investors’ fantasies were exposed for what they were and any basis of trust in the market was now destroyed.

By the end of August 2015 the market had fallen to under 3000 despite the strenuous efforts to reverse its direction by the Chinese government. After a brief recovery, the market fell again by no less than 25% again in the month of January 2016 to its lowest level in 14 months. Fundamentals may superficially be viewed as somewhat consistent with a rational explanation for this further market collapse (although by a quarter in a month?) with the Chinese economy continuing to slow down and concerns that the rescue measures implemented by the Chinese government to prevent the market declining further would expire. However, probably more salient was the fall in investor trust in the market associated with the implementation of circuit breaker trading restrictions on the 3rd January, although cancelled five days later, leading to the concern that investors would be locked in if the market dropped below one of pre-set threshold values. Also, the inevitable lack of belief now in the Chinese government’s ability to engineer any market rebound given how investors had been burnt twice! Mentions of further government intervention increase during this period.

Figures 5 and 6 here

Based on this initial analysis our general theme that there is a clear relationship between investors' different emotional states and what they experience during an asset pricing bubble is confirmed. This evidence is also consistent with the idea that in such speculative bubbles investors appear to believe they have been given licence to search for and find the phantastic object. On this basis we suggest that the associated visceral investor passions and antipathies unleashed in this process can be a key driver of asset pricing in bubble markets. Our specific hypotheses are tested using our data in the following sub-sections.

6. The relation between investor emotions and stock returns

In this section we explore empirically the relation between emotions and stock returns, and also the two-way causality issue using out-of sample data: do investors' fantasies and associated emotions drive prices in asset pricing bubbles, is it the other way around, or is any relationship mainly endogenous? *Inter alia*, we show how it is possible to build an empirical model to measure the dynamic interplay of powerful investor emotions and their causal relationship with market prices and then use this to forecast the SSECI in an out-of-sample period.

6.1. Contemporaneous regressions

To test our first hypothesis that market returns and market emotional states are closely associated, we first run the following OLS regression:⁶

$$r_t = \beta_0 + \beta_2 emotion_t + \varepsilon \quad (2)$$

where:

$$r_t = \left(\frac{SSECI_t}{SSECI_{t-1}} \right) - 1,$$

Emotion_t = One of mania, excitement, happy, worry, anxiety, panic, and revulsion measured during month t.

⁶ Given the evidence in table 1 of high correlations between the emotional states, we use only one emotion at a time in our regressions.

6.2. The nature of any potential causality

This paper develops a dynamic five-phase emotional trajectory theory of asset pricing bubbles which revolves around the idea that investors are caught up emotionally, and that it is these powerful emotions that drive market prices. However, the nature of the relationship between investor emotions and market behaviour is a subtle one in that in a stock market bubble the financial media will be reporting both the dramatic market movements, and also the associated behaviour of investors. In addition, financial journalists themselves are likely to be caught up in the high levels of excitement as the bubble inflates and subsequent panic when it bursts. Such processes are clearly reflexive in nature. Similarly, investors will be observing movements in the market and also reacting to its coverage in the media and this, we hypothesise, will lead to them being sucked into the underlying fantasy even more deeply. How can we disentangle all these different interrelated relationships?

An alternative perspective to our investor fantasy-driven theory is taken by Shiller (2015, chapter 10) who argues bubbles are not driven by investor “craziness” but by social contagion and that it is news of price increases that drives investors to invest more and more leading to the bubble (Shiller’s theory does not address the bursting of bubbles and subsequent dramatic collapse in prices). In this section, we specifically test these two alternative theories of investor behaviour. To what extent was the 2014-2016 Chinese stock market bubble driven by investor emotions as reflected in the media, and to what extent were investor emotions driven by the bubble itself? What is the underlying nature of any potential endogeneity?

To distinguish between these two alternative explanations for the recent Chinese stock market bubble statistically, we need to choose a proper model. First, it has to consider potential two-way causality, i.e., dramatic movements in the SSECI can drive the tenor and emotional nature of journalist reporting while powerful investor emotions, as reflected in media market coverage, can affect the SSECI through the actions of investors. Second, the model needs to have some ability to forecast the SSECI in bubble market conditions.

To test whether investor emotions predict market returns or whether it is the extreme market movements that generate powerful investor emotions we employ a vector autoregressive (VAR) model approach. Specifically, since all variables in the VAR are dependent variables, this allows us to explore the direction of causality between different investor emotions and movements in the SSECI. In addition, as we will see, since all

variables on the right hand side of our VAR regression function are lagged, the model can be used for forecasting as well.

6.3 Building our model

To construct our VAR model we first use the AIC, HQIC and SBIC measures to determine the optimal lag for our data, and find a one-period lag to be most appropriate. We also examine the stability of our model using the Lagrange-multiplier test and the roots of the companion matrix and find our one-period lag model to be stable. Our VAR model takes the following form with independent variables consisting of prior month return, and the seven emotions lagged one month: mania, excitement, happy, worry, anxiety, panic, and revulsion and is used to predict log of next month's return:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 emotion_{t-1} + \varepsilon \quad (3)$$

$$emotion_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 emotion_{t-1} + \varepsilon \quad (4)$$

Where the variables are as defined in equation (2)

6.4 Results

Table 2 presents the results of contemporaneous regressions of equation (2). This confirms the relations observed in table 1, positive emotions have positive coefficients and negative emotions coefficients in a formal regression framework. Further, our three composite measures also have highly significant positive coefficients.

Table 2 here

The results in table 2 provide support for our first hypothesis, between 2014 and 2016, Chinese stock market returns and market emotional states are closely associated.

Table 3 presents the results of vector autoregression models executed with one emotion at a time. Panel A of table 3 explores to what extent investor emotions are driven by the market. It shows strong evidence that mania is driven by index returns in the previous month ($t = 3.00$), and some weak evidence for revulsion ($t = 1.76$). However, it also shows that other emotions are not driven by the prior month returns. These results thus present some

evidence consistent with our second hypothesis in the case of mania and revulsion providing some support for Shiller's (2014) social contagion argument.

Panel B of table 3 explores whether emotions drive market returns. This shows that excitement in the previous month is positively related to the stock return one month ($t = 1.88$) ahead while anxiety ($t = 1.65$) and panic ($t = 2.14$) are negatively related to subsequent month returns. Other emotions do not show any predictive ability for next month returns. Of the three composite measures, the variable based on the relative excitement and anxiety levels $((E-A)/(E+A))$ has the strongest relation with subsequent month returns ($t = 2.19$). On this basis we have evidence consistent with our third hypothesis i.e., that investor emotions are driving market returns during the recent Chinese stock market bubble.

Table 3 here

In summary, table 3 suggests that investor emotions are far more powerful in driving the SSECI during the 2014-2016 Chinese stock market bubble than the other way around and provide support for our emotional trajectory theory of asset pricing bubbles. To explore these results further we also conduct Granger causality tests presented in table 4. The results show which show that whereas prior period excitement, anxiety, panic, and our main composite variable that measures relative excitement and panic predict the SSECI returns in the next period, the SSECI returns only seems to be able to predict the level of investor mania. Our empirical results suggest that it is investor fantasy and associated emotional states that appear to be driving next month SSECI returns during the 2014 to 2016 Chinese stock market bubble more than that investor fantasy is driven by the SSECI returns itself. As such we do not have any evidence consistent with hypothesis H2, and quite strong evidence for H3, i.e., the direction of causality is much stronger in the case of emotions driving prices rather than the other way around.

Table 4 here

Finally, we test our fourth hypothesis as to whether weak emotion words such as happy and worry have the same power as our strong emotion words: excitement and anxiety. Figure 7 plots the ratio of our happy to worry variables against the concurrent month returns on the SSECI. As can be seen this measure seems largely insensitive to changes in the

Shanghai Stock Exchange Index in contrast to our general media tone measure $((E-A)/(E+A))$ ($[\text{excitement} - \text{anxiety}]/[\text{excitement} + \text{anxiety}]$) plotted in figure 4 which closely reflect markets movements. The VAR results table 3 panel B also show that our composite variable that measures relative happiness and worry $((H-W)/(H+W))$ is not able to predict next month returns ($t = 1.00$).

As such, we find evidence consistent with our fourth alternate hypothesis, i.e., that more powerful emotion words dominate weaker emotion ones in measuring investor emotional states and their relationship with market returns during asset pricing bubbles.

Figure 7 here

6.5 Trading with investing emotions

However, to test our theory more directly, the key question is how well our model predicts out of sample. To this end we implement a trading strategy based on our composite variable that measures relative excitement and anxiety. We implement two separate strategies: (1) go long in the months when excitement exceeds anxiety in the previous month, exit the market in other months, as it is not possible to short in the Chinese market, and (2) go long when excitement exceeds anxiety in the previous month, and short when anxiety exceeds excitement. Results presented in table 5 show that the long only strategy earns 2.67% per month as compared to a 1.68% return on the SSECI during this period while the long-short strategy earns 3.65% per month. Results not tabulated here also show that the difference between excitement and anxiety has the ability to identify the direction of next month stock market movement. It correctly identifies positive movement in 13 out of the 19 months. The two-way contingency table shows some weak evidence of association between our composite measure and subsequent stock returns ($\chi^2 = 2.91$, $p = 0.09$).

Table 5 here

Figure 8 plots the SSECI index (rebased to 100) and the return to the trading strategy using the excitement and anxiety compound variable. It shows that as the market came off the peak

in May 2015, and the level of anxiety exceeded that of excitement, the strategy was able to generate positive returns even though the market fell through to July 2016.

Figure 8 here

7. Robustness checks

We repeat our analyses for the earlier Chinese stock market bubble of 2005-2008. Results not tabulated here show our main results hold in the earlier period as well. Similar to the results reported in table 2 here, positive emotions with the exception of “Happy” and the composite variables are significantly positively related to contemporaneous returns while negative emotions are significantly negatively related. Further, Granger causality tests show that “Excitement” and the composite variable capturing relative excitement and anxiety $((E-A)/(E+A))$ Granger cause returns though there is also some weak evidence that returns Granger cause the composite variable. The weaker emotions composite variable $((H-W)/(H+W))$ does not Granger cause returns though the reverse is true. The long-short trading strategy earns 2.44% per month and does better than the 1.67% per month earned by the index in the first period though the contingency table test is unable to reject the null hypothesis of no association between the positive/negative composite variable and positive/negative returns in the next month.

8. Discussion and conclusion

This paper sets out to explain the recent Chinese stock market bubble of 2014 – 2016 in terms of the underlying emotional processes at work. Traditional explanations of financial bubbles tend to focus on theoretical and analytical models that may or may not actually fit the real-world experience of investors in real world markets. However, by considering the emotional drivers of investor behaviour in such highly charged situations and formally recognising the powerful and potentially debilitating fantasies and emotions unleashed in speculative bubbles, we argue we can increase our understanding of such major destructive economic

events. In this paper we adopt a formal content analysis approach. Using emotion key word dictionaries which we develop specifically for our particular purpose we demonstrate how Chinese market participants' emotional fantasies, anxieties and drives, fanned by the Chinese government and media, led asset prices to depart dramatically from underlying fundamental value in a very compressed timeframe. Adopting a well-established path-dependent model of investor emotions based on the original Minsky taxonomy of bubble activity, we show that the search by investors for what we term a phantastic object can help explain the morphology of the Chinese stock market bubble as it played out. In this process warning voices are ignored as investors become carried away in their wish fulfilling fantasy of a market that only moves in one direction which is rapidly up, and the wealth they believe will result. Mania and euphoria reign until eventually it is no longer possible for investors to continue to deny the siren voices and reality intrudes. The bubble bursts and panic ensues with investors trying to dump their now devalued stocks as quickly as possible before prices fall further. Revulsion and blame follow together with the search for scapegoats, and in the bubble which is the focus of this paper, the Chinese government's very expensive but ultimately fruitless attempts prevent the stock market from imploding further.

In contrast to many economists who view bubbles as an underlying fact of life which cannot be explained, based on our detailed empirical analysis we argue that, in fact, asset pricing bubbles are perfectly explicable. This follows if, instead of looking for patterns of rational economic activity, we recognise that most financial decisions, as with most other decisions we make, are predominantly emotional in nature. Only in this way are economists and policymakers going to be able to understand the nature and morphology of financial bubbles in the future and be in a better position to take appropriate action.

In our content analysis we show how the Chinese media directly mirrors investor emotions in the speculative situation we explore. Ultimately we are dealing with a highly dynamic process with our empirical VAR analysis and Granger causality tests showing how the SSECI was being largely driven by investor fantasy as reflected in market emotional states rather more than the powerful investor emotions being reported on in the media simply reflecting, or being driven by, dramatic movements in market prices. Future work can perhaps look in more detail at potential emotion variable warning signs of sudden reversal in the market trajectory in bubble environments and subsequent sharp deflation in prices.

As we show in our robustness tests the 2014-2016 Chinese stock market bubble has similar emotional dimensions to the 2005-2008 Chinese stock market bubble of only a few years earlier as figure 9 illustrates. The results of our parallel analysis of the earlier bubble are very similar and thus also provide an independent test of the robustness of our research approach. It seems that Chinese investors, at least, have short memories and are unable to learn from experience so emotionally seductive and exciting speculative bubbles are. In addition, we repeat both sets of analyses using non-Chinese media in English and parallel domain-specific emotion key word dictionaries, and again we find similar emotional processes being picked up although a little attenuated in comparison which is what we would expect. This is because Western financial journalists were not caught up directly in the stock market bubble in the same way as Chinese financial journalists were and, as such, any emotional engagement would be less charged. This is indeed, in fact, what we find in our content analysis and empirical results. Further work needs to test our emotional model of bubbles in other cases such as dot.com mania adopting a similar research approach.

Figure 9 here

We conclude by arguing the need explicitly to take investor fantasy and associated emotions into account not just in the case of speculative bubbles but also potentially in seeking to explain investor behaviour in non-bubble situations more generally.

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Table 1: Correlation matrix: Emotions and Shanghai Stock Exchange Composite Index 2014-2016

The correlations are between the standardized emotions estimated over the month and the returns on the SSECI during the same month (return_t), previous month (return_{t-1}), and the subsequent month (return_{t+1}). The standard deviation for a month is estimated using the daily returns on the index during that month. The data covers the period January 2014 to June 2016.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Mania	1														
(2) Excitement	0.56	1													
(3) Happy	0.14	0.54	1												
(4) Worry	-0.39	-0.75	-0.36	1											
(5) Anxiety	-0.13	-0.66	-0.55	0.71	1										
(6) Panic	-0.06	-0.65	-0.47	0.58	0.89	1									
(7) Revulsion	-0.30	-0.66	-0.29	0.62	0.80	0.75	1								
(8) Ret_{t+1}	-0.05	0.45	0.36	-0.22	-0.42	-0.47	-0.18	1							
(9) Ret_t	0.43	0.75	0.41	-0.66	-0.71	-0.74	-0.58	0.32	1						
(10) Ret_{t-1}	0.62	0.39	0.14	-0.25	-0.32	-0.33	-0.52	-0.09	0.33	1					
(11) Stdev_{t+1}	0.54	-0.04	-0.21	0.07	0.44	0.56	0.17	-0.53	-0.11	0.12	1				
(12) Stdev_t	0.29	-0.42	-0.27	0.48	0.84	0.85	0.66	-0.42	-0.51	-0.09	0.69	1			
(13) Stdev_{t-1}	-0.06	-0.49	-0.11	0.42	0.62	0.60	0.62	-0.16	-0.40	-0.49	0.42	0.69	1		
(14) $(E-A)/(E+A)$	0.34	0.89	0.61	-0.79	-0.92	-0.84	-0.81	0.48	0.77	0.38	-0.29	-0.70	-0.62	1	
(15) $(H-W)/(H+W)$	0.34	0.78	0.81	-0.84	-0.76	-0.63	-0.55	0.34	0.66	0.25	-0.15	-0.45	-0.32	0.85	1
(16) $(M-P-R)/(M+P+R)$	0.79	0.87	0.52	-0.63	-0.60	-0.58	-0.66	0.30	0.69	0.64	0.12	-0.22	-0.37	0.79	0.71

Table 2: Contemporaneous regressions

The table reports the results of the following OLS regressions:

$$r_t = \beta_0 + \beta_2 emotion_t + \varepsilon \quad (2)$$

Where r_t is the return on SSEC1 during month t , and the $emotion_t$ is standardised value of one of the seven emotions or one of the three composite variables estimated during month t . p refers to the p -value of the overall F-statistics of the individual regressions. The data covers the period January 2014 to June 2016.

	Constant	t	Coeff	t	Adj R ²	p
Mania	-0.045	(-1.61)	20.621	(2.55)	0.160	0.017
Excitement	-0.198	(-5.35)	47.466	(6.03)	0.550	0.000
Happy	-0.257	(-2.22)	11.330	(2.36)	0.137	0.025
Worry	0.404	(4.79)	-26.142	(-4.66)	0.417	0.000
Anxiety	0.179	(5.40)	-42.474	(-5.30)	0.483	0.000
Panic	0.137	(5.70)	-34.002	(-5.76)	0.526	0.000
Revulsion	0.155	(3.95)	-222.732	(-3.81)	0.318	0.001
(E-A)/(E+A)	-0.003	(-0.25)	0.233	(6.30)	0.572	0.000
(H-W)/(H+W)	-0.110	(-3.67)	0.535	(4.60)	0.410	0.000
(M-P-R)/(M+P+R)	0.050	(3.60)	0.179	(5.08)	0.461	0.000

Table 3: Vector Auto Regression analysis

Panels A and B report the results of the following VARs respectively:

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 emotion_{t-1} + \varepsilon \quad (3)$$

$$emotion_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 emotion_{t-1} + \varepsilon \quad (4)$$

Where r_t is the return on SSECI during month t , and the $emotion_t$ is standardised value of one of the seven emotions or one of the three composite variables estimated during month t . p refers to the p -value of the F-statistics of the individual regressions. The data covers the period January 2014 to June 2016.

A. $Emotion_t = \alpha + \beta_1 Return_{t-1} + \beta_2 Emotion_{t-1}$								
	Constant	t	Return _{t-1}	t	Emotion _{t-1}	t	R ²	p
Mania	0.001	(2.83)	0.008	(3.00)	0.571	(4.64)	0.645	0.000
Excitement	0.002	(1.67)	-0.002	(-0.50)	0.638	(2.79)	0.321	0.001
Happy	0.012	(2.82)	-0.003	(-0.51)	0.503	(2.84)	0.228	0.014
Worry	0.009	(2.47)	0.000	(0.07)	0.424	(1.85)	0.168	0.054
Anxiety	0.001	(1.37)	0.003	(0.72)	0.678	(3.17)	0.337	0.001
Panic	0.001	(0.94)	0.005	(0.97)	0.734	(3.32)	0.353	0.000
Revulsion	0.000	(3.47)	-0.001	(-1.76)	0.319	(1.72)	0.334	0.001
(E-A)/(E+A)	0.027	(0.64)	-0.942	(-1.34)	0.861	(4.02)	0.448	0.000
(H-W)/(H+W)	0.097	(1.85)	-0.180	(-0.68)	0.594	(2.71)	0.249	0.008
(M-P-R)/(M+P+R)	-0.088	(-1.56)	0.848	(1.33)	0.584	(3.51)	0.581	0.000

B. $\text{Return}_t = \alpha + \beta_1 \text{Return}_{t-1} + \beta_2 \text{Emotion}_{t-1}$

	Constant	t	Return_{t-1}	t	Emotion_{t-1}	t	R^2	p
Mania	0.043	(1.43)	0.422	(2.23)	-11.035	(-1.21)	0.148	0.081
Excitement	-0.117	(-1.67)	-0.033	(-0.13)	29.816	(1.88)	0.202	0.026
Happy	-0.178	(-1.43)	0.205	(1.12)	7.964	(1.54)	0.172	0.049
Worry	0.016	(0.11)	0.317	(1.35)	-0.263	(-0.03)	0.105	0.184
Anxiety	0.107	(1.80)	0.045	(0.19)	-23.412	(-1.65)	0.182	0.040
Panic	0.103	(2.28)	-0.058	(-0.24)	-23.743	(-2.14)	0.226	0.014
Revulsion	0.007	(0.12)	0.333	(1.55)	7.603	(0.09)	0.105	0.183
(E-A)/(E+A)	0.005	(0.33)	-0.100	(-0.40)	0.167	(2.19)	0.231	0.013
(H-W)/(H+W)	-0.031	(-0.68)	0.169	(0.74)	0.190	(1.00)	0.134	0.106
(M-P-R)/(M+P+R)	0.021	(0.97)	0.217	(0.89)	0.039	(0.62)	0.116	0.148

Table 4: Granger causality tests

The table reports the results of the Granger causality tests for the VAR in table 3. The data covers the period January 2014 to June 2016.

Emotion	A. Returns Granger cause emotions		B. Emotions Granger cause returns	
	Chi-sq	p	Chi-sq	p
Mania	8.985	0.003	1.474	0.225
Excitement	0.249	0.618	3.534	0.060
Happy	0.262	0.609	2.367	0.124
Worry	0.005	0.945	0.001	0.978
Anxiety	0.515	0.473	2.726	0.099
Panic	0.935	0.334	4.560	0.033
Revulsion	3.099	0.078	0.009	0.926
(E-A)/(E+A)	1.790	0.181	4.776	0.029
(H-W)/(H+W)	0.465	0.495	0.991	0.319
(M-P-R)/(M+P+R)	1.780	0.182	0.385	0.535

Table 5: Return on strategy based on $(E-A)/(E+A)$

The table reports the average monthly returns on the SSECI Between February 2014 and July 2016, and on two trading strategies. Long only refers to the average monthly returns on a trading strategy that invests in the SSECI if in the previous month, the value of the $((E-A)/(E+A))$ variable is negative, otherwise it is disinvested and earns 0 return. Long & Short refers to the average monthly returns on a trading strategy that goes long on the SSECI if in the previous month, the value of the $((E-A)/(E+A))$ variable is negative, otherwise it goes short. The data covers the period January 2014 to June 2016.

	Average monthly return (%)	Monthly standard deviation	Number of months with positive returns	Number of months with negative returns
Full period	1.68	8.97	19	11
Long only $[(E-A)/(E+A)]>0$	2.67	5.97	13	4
Long & Short	3.65	8.34	20	10

Figure 1: Shanghai Stock Exchange Composite Index: An emotional trajectory

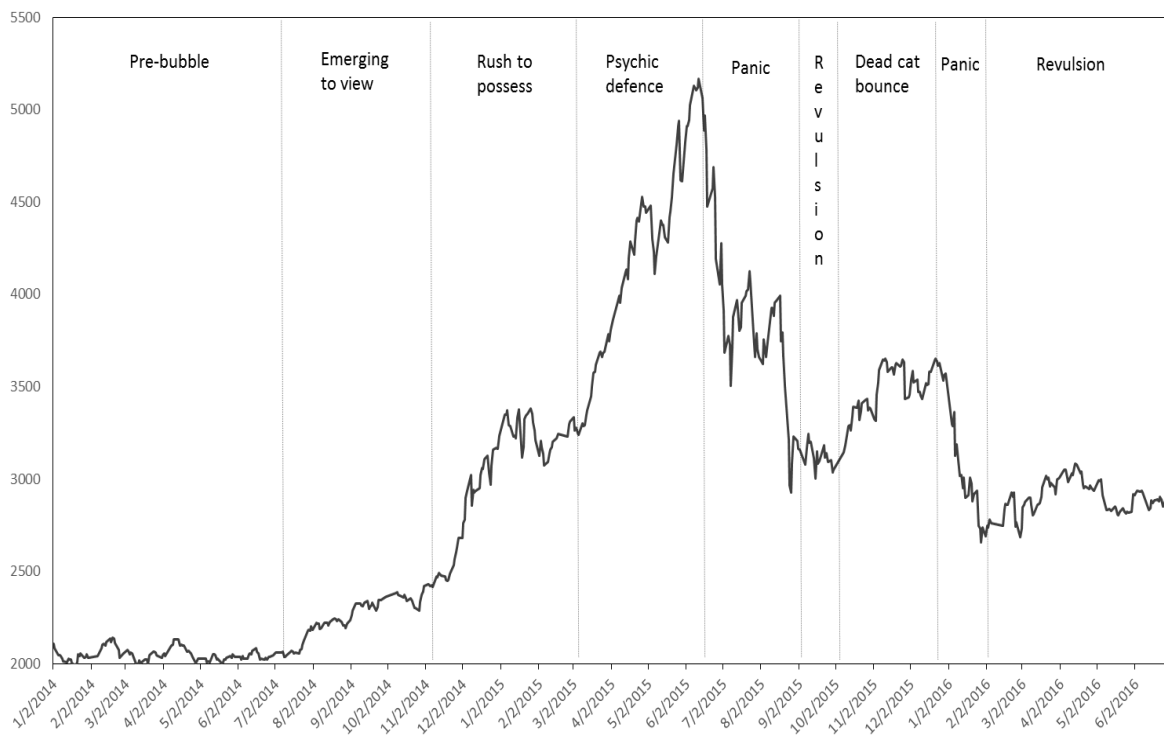


Figure 2: SSECI (daily) vs monthly standard deviation 2014 – 2016

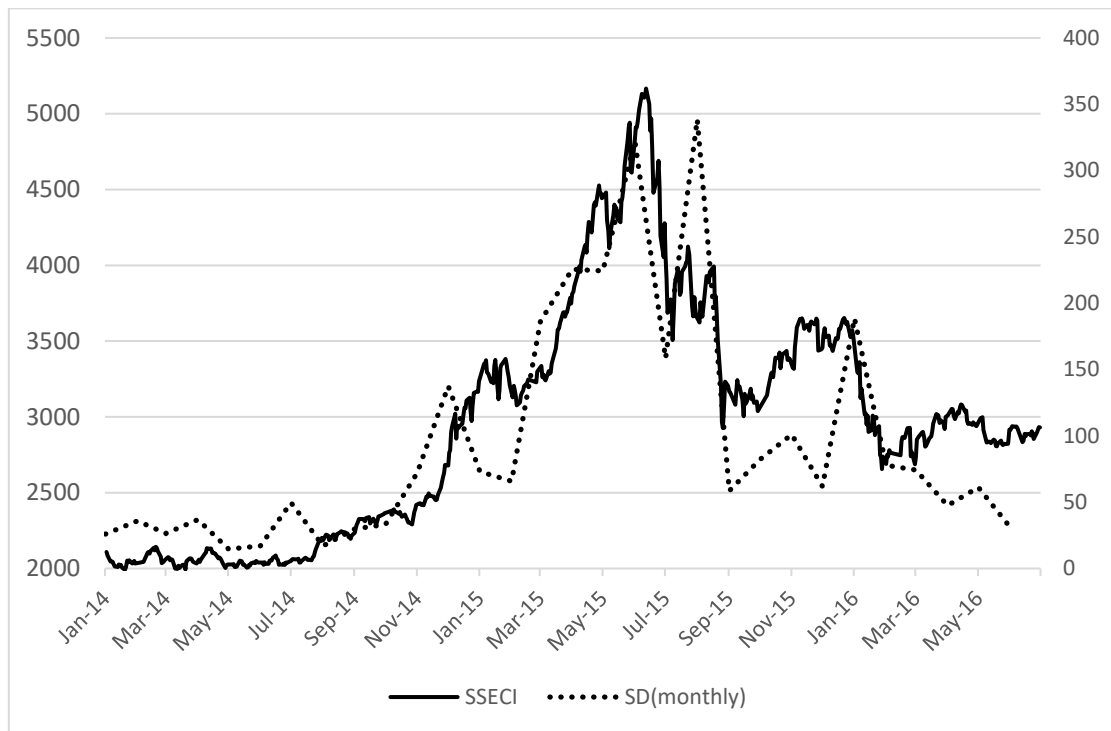


Figure 3: SSECI vs Monthly Market Turnover Ratio (H1 2014 = 1) (r = 0.91)

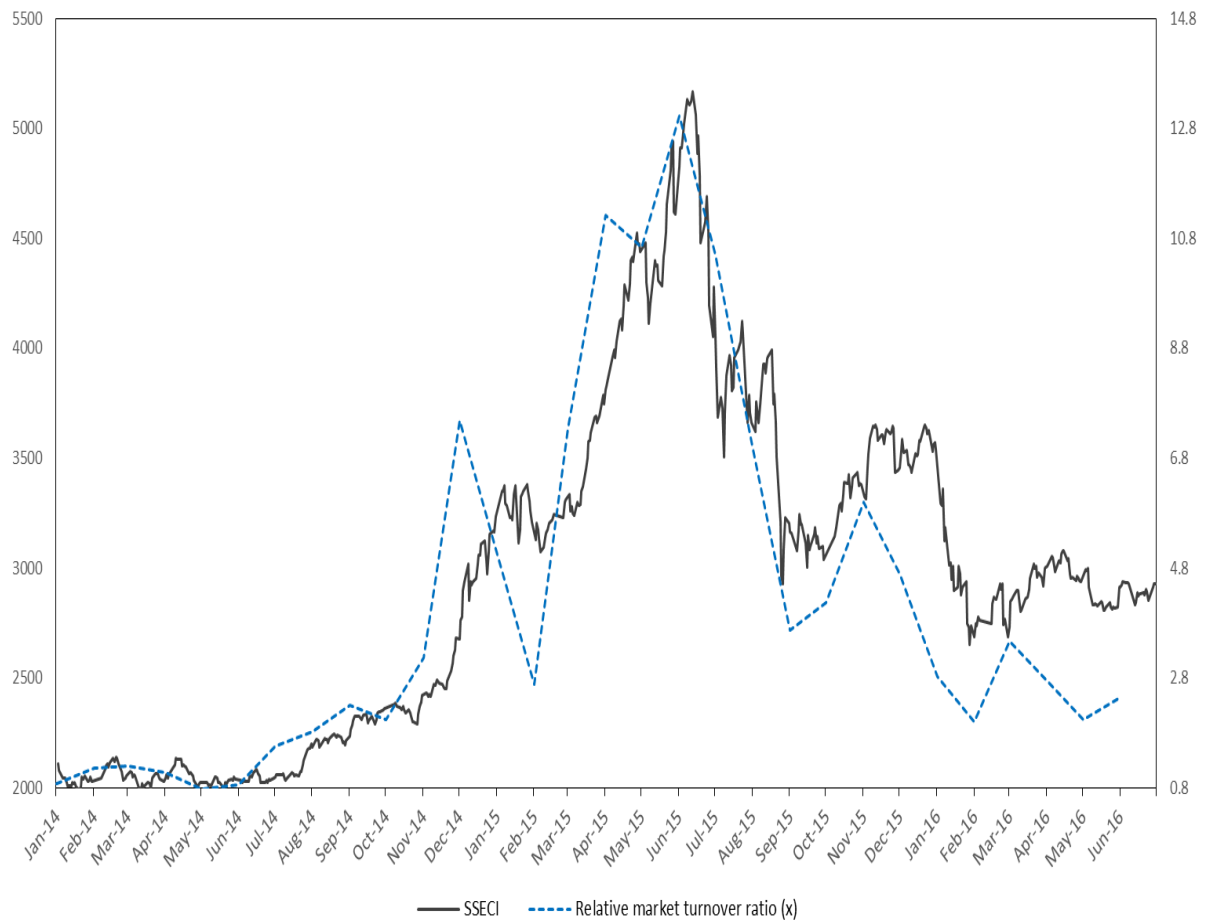


Figure 4: SSECI returns v $(E-A)/(E+A)$

The figure plots the monthly return on the SSECI from January 2014 to June 2016 against the composite variable during the same month estimated as $(Excitement - Anxiety)/(Excitement + Anxiety)$.

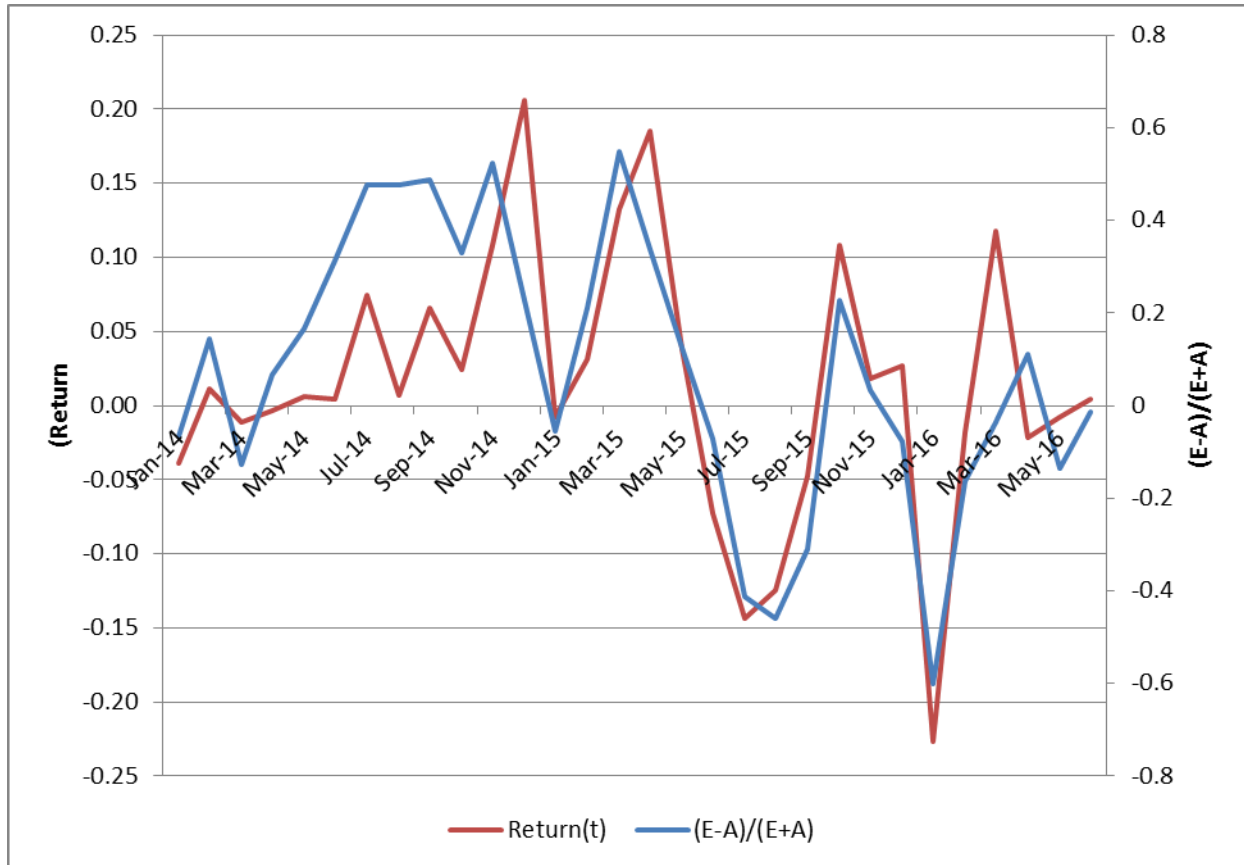


Figure 5: Standardized frequency of "Bubble" type of emotion words against SSECI

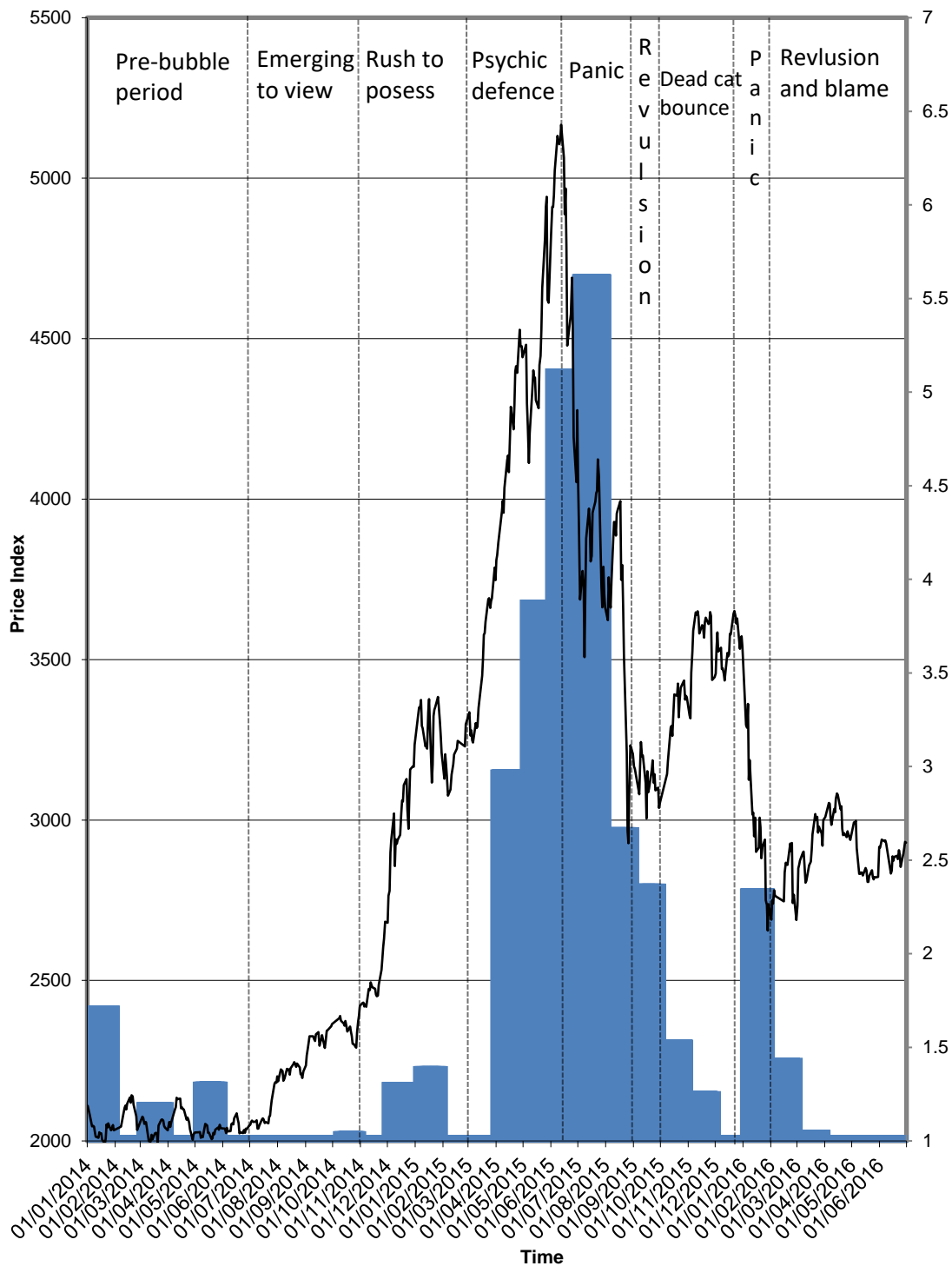


Figure 6: Standardized frequency of "Government Intervention" type of emotion words against SSECI

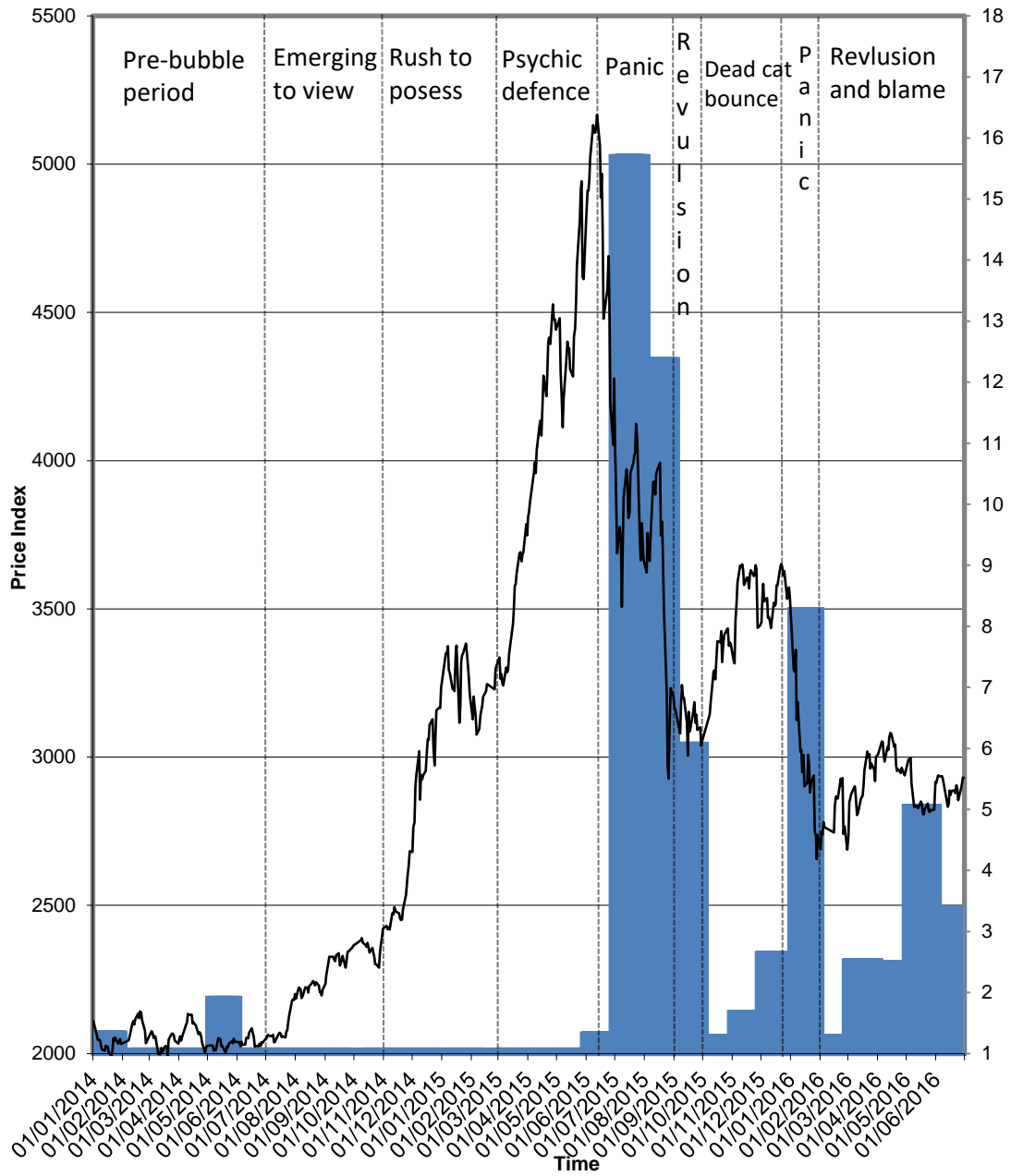


Figure 7: SSECI returns v $(H-W)/(H+W)$

The figure plots the monthly return on the SSECI from January 2014 to June 2016 against the composite variable during the same month estimated as $(Happy - Worry)/(Happy + Worry)$.

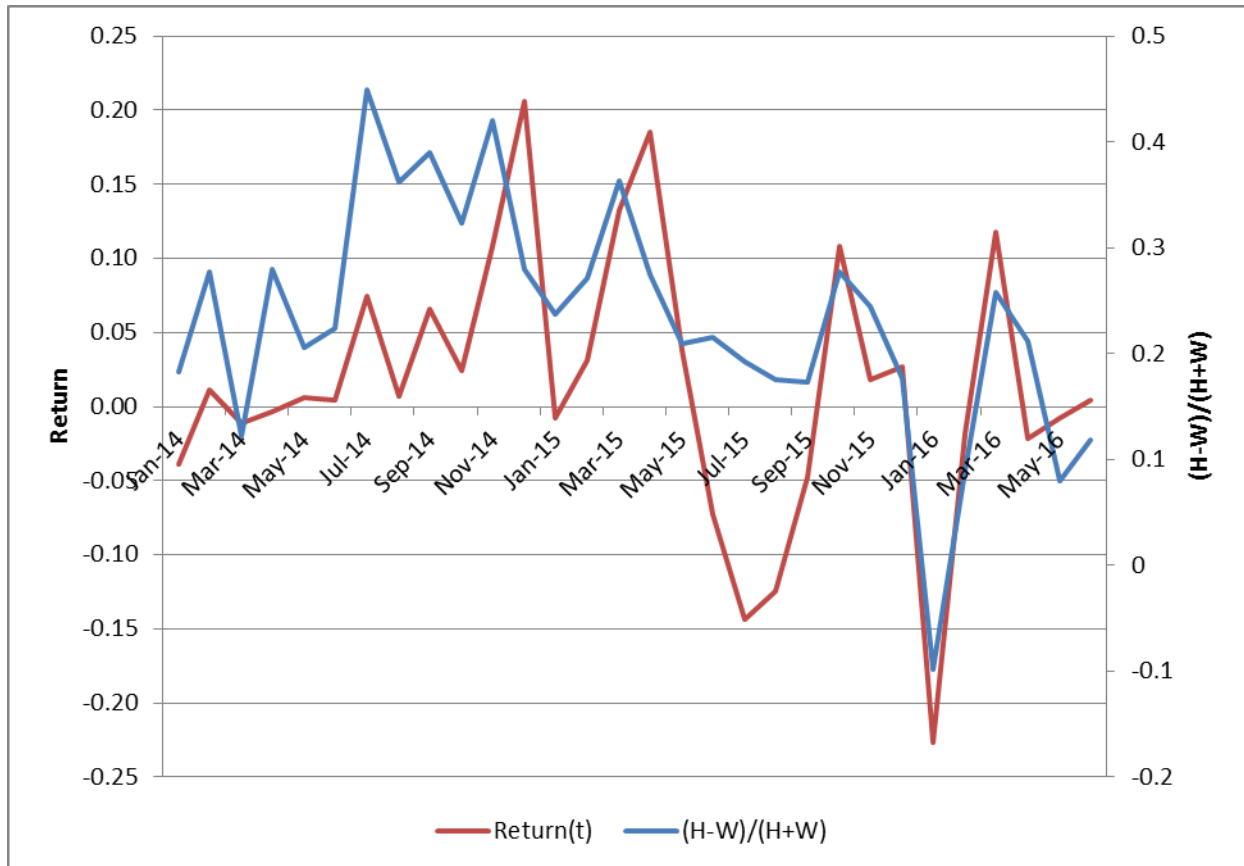


Figure 8: SSECI returns v Returns on $(E-A)/(E+A)$

The figure plots the value of RMB100 invested in the SSECI at the end of January 2014 against the value of RMB100 invested in the Long & Short strategy of table 5 over the same time period. The strategy goes long on the SSECI if in the previous month, the value of the $((E-A)/(E+A))$ variable is negative, otherwise it goes short.

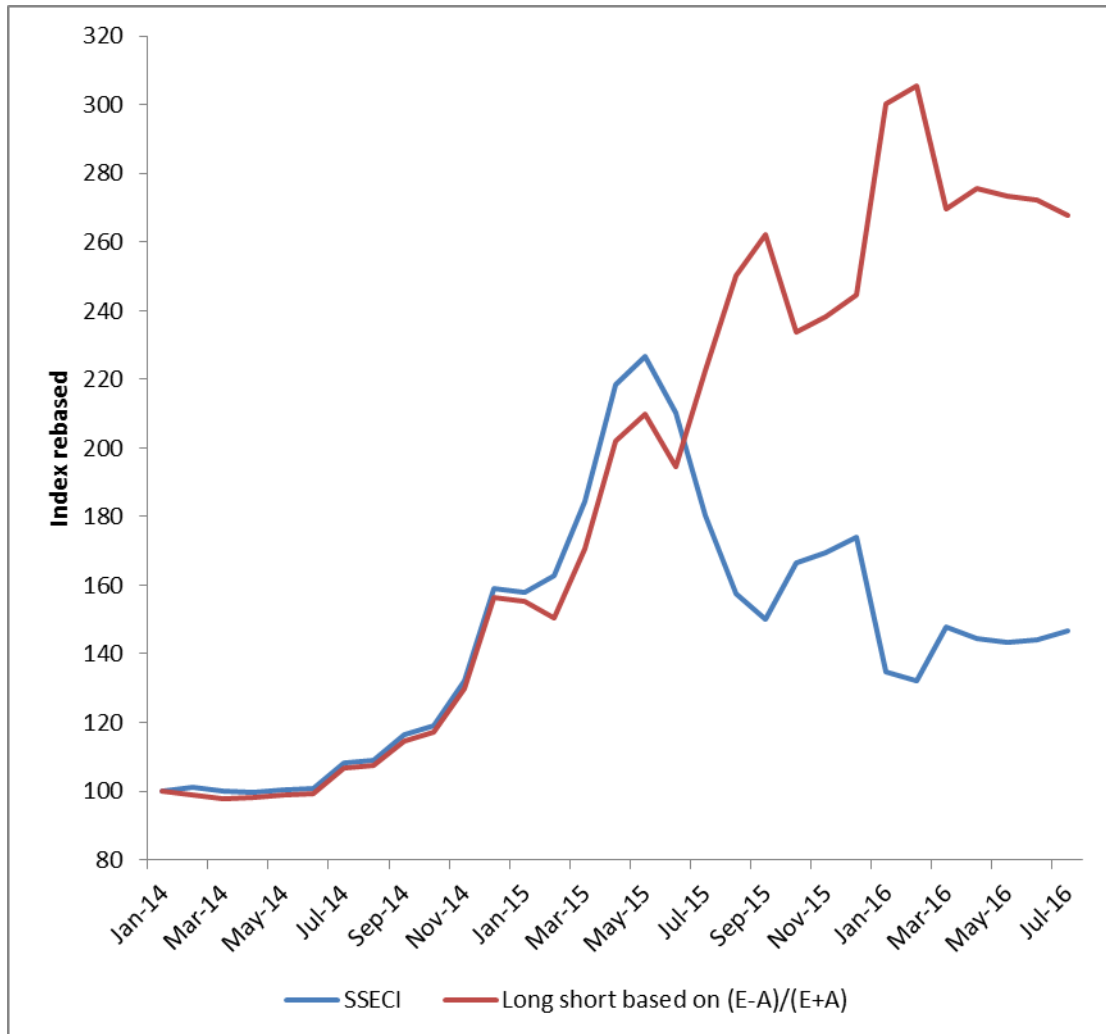


Figure 9: SSECI from 2005 to 2016

