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CONVENTIONAL VIEWS AND ASSET PRICES: WHAT TO EXPECT AFTER TIMES OF EXTREME OPINIONS?

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This study evaluates the performance of stock market indices after times of extreme opinions. The underlying conjecture is that extreme opinions are associated to overreactions in the perception of wealth. The analysis covers 34 countries from 1988 through 2013. In a novel approach, views regarding economic performance are approximated using content in the global economic press. Consistent with the overreaction conjecture, stock market indices are shown to under-perform following extreme optimistic views and over-perform after pessimistic views. A long-short contrarian portfolio earns 11% annually over the next five years. This persistent and predictable difference in returns cannot be explained by risk considerations and cannot be replicated using alternative strategies based on past returns or past economic growth.

JEL classification codes: G12, G17, D84
Key words: asset prices, opinions, expectations, overreaction.

I. Introduction

In November 2009, the weekly magazine *The Economist* ran a cover in which the title "Brazil takes off" was accompanied by a *statue* of Christ the Redeemer ascending like a rocket from Rio de Janeiro's Corcovado mountain. This strong sign of optimism was later reversed in September 2013 when the cover asked "Has Brazil blown it?"

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together with a picture of a collapsing statue-rocket.[1] As eloquently exemplified by the pair of covers, opinions regarding economic prospects are regularly seen to enter stages of high hopes or, in other occasions, periods of intense gloom. Determining the accuracy of these emergent judgments is a matter of interest. This is because important economic decisions by private and public actors can benefit from a better understanding of the information conveyed by conventional views.

Conventional views are understood as a set of beliefs that are broadly shared, are known to be shared and so on. In this work, the focus is placed on broadly shared views regarding economic conditions. For example, beliefs regarding future economic prosperity or the evolution of aggregate productivity. Importantly, the public condition of this set of beliefs implies that they are observable and can be approximated, for example, analyzing contents in the economic press.

The underlying assumption behind this work is that the evolution of these public beliefs are strongly linked to the path of asset prices in an economy. More specifically, one plausible conjecture is that extreme conventional assessments are associated to excessive responses. Under this conjecture, the occasional emergence of extreme shared opinions could be linked to mispricing of broad classes of assets and predictable errors in saving and investment decisions. Despite its relevance, formal empirical evidence of this conjecture is hindered by lack of sufficiently comprehensive and precise measures of conventional views.

In this work, this conjecture is empirically evaluated for the case of financial assets. The performance of stock market indices is evaluated after times of extreme optimism and extreme pessimism. The study covers 34 countries from 1988 through 2013. One distinctive aspect of this work is the approximation of conventional views using content published in the international economic press.

Consistent with the postulated conjecture, the results show that optimism is followed by lower mean returns and pessimism by higher mean returns. This difference in performance is highly persistent and economically significant. A long-short contrarian portfolio earns 11% annually over the next five years. Additionally, it is found that the performance of sentiment based portfolio strategies cannot be replicated using information on past returns or past economic growth. Finally, the findings suggest that changes in anticipated risk levels are not a good explanation of the reported return differentials.

A natural interpretation of these findings is that the occasional emergence of conventional views regarding economic prospects generates mispricing for a broad

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[1] See *Economist* (2009) and *Economist* (2013).

set of assets. Contributions associated to social learning can help rationalize these events. The well-established literature on social learning has shown that information can be aggregated quite inefficiently.[2] Complementarily, social learning can lead to more severe inefficiencies if agents follow simple rules that ignore redundancies in public information[3] or if a subset of actors is too influential.[4] Additionally, the existence of return predictability based on publicly available information suggests the presence of individuals that process information in an incomplete and correlated manner.[5]

The recurrent, persistent and predictable overreactions documented in this study have important implications that go beyond financial markets. Given the key function of asset prices in the aggregation of information and the coordination of actions, the results are relevant for the understanding of macroeconomic dynamics and public policy that aims for stability.

One key assumption of the current study is the idea that conventional views regarding economic prospects can be approximated processing information in the economic press. This idea is supported by the dual role of the media. The economic press publishes information that reflects and, at the same time, shapes public opinion. It is worth noting that press content is selected based on journalists' or editors' beliefs regarding dominant public opinions. In this context, confirming public opinions might be a profitable marketing strategy.[6] Additionally, it is reasonable to assume that an important fraction of the content is forward looking. For example, the inspection of some distant episode might be linked to its relevance given current opinions.

The reported findings show that empirical studies that focus on subjective states can advance the understanding of economic dynamics. This is a natural outcome once it is recognized that economic processes emerge as the result of the co-evolution of structural and subjective elements. According to this perspective, subjective elements cannot be inferred through logical deductions and there is value in finding estimations of these elements that can allow for new insights.

This study is related to a fertile body of theoretical and empirical contributions that calls attention to the role of expectations, learning and coordination in financial

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[2] See for example Banerjee (1992) and Bikhchandani et al. (1992).

[3] Eyster and Rabin (2010, 2014).

[4] Golub and Jackson (2010).

[5] Models of cognitive limits or simple responses can be found, for example, in Mullainathan (2002), Hong and Stein (1999) and Brock and Hommes (1998). Conceptual analyses in this line can also be found in Kindleberger and Aliber (2011) and Shiller (2005).

[6] See for example Mullainathan and Shleifer (2005) and Gentzkow and Shapiro (2010).

and macroeconomic dynamics. Using theoretical models, learning dynamics about structural parameters have been explored as a source of aggregate fluctuations.[7] Additional sources of non-fundamental volatility are suggested by models with strategic complementarities and multiple equilibria. In these analyses, under-determination of equilibrium can be interpreted as an indication that, inevitably, beliefs are a distinct element in the determination of economic outcomes.[8] Complementarily, the literature on herd behavior has shown that information can be aggregated inefficiently and, as a result, aggregate beliefs and behavior can be quite idiosyncratic.[9] In financial markets, models of limits to arbitrage have shown that market participants might be unable or unwilling to implement trading strategies that transmit information to asset prices.[10] Importantly, further sources of non-fundamental volatility emerge once cognitive limits and simple mental models are allowed for.[11]

In a related contribution, Dumas et al. (2011) show that some well-known anomalies observed in international equity markets can be explained by a model in which agents perceive differences in the precision of information regarding local and foreign markets.

This article is also connected to the well-known empirical literature that shows evidence consistent with inefficiencies, excess volatility and overreaction in stock markets. Most of these analyses focus on firm level returns and use historic information on asset prices, financial statements and market activity.[12] More closely related to the current study, some contributions focus on the dynamic relationship of aggregate proxies for investor sentiment and stock returns.[13] In these contributions, the proxies are based on consumer confidence surveys and financial market outcomes. In a related analysis of international equity markets, Hwang (2011) finds that sentiment toward countries, as inferred from public opinion surveys, is associated to demand for securities and distortions in asset prices.

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[7] For example, see learning models in Sargent (1993), Heymann and Sanguinetti (1998) and Milani (2007).

[8] See Diamond (1982), Cooper and John (1988) and Obstfeld (1996).

[9] For early contributions see Banerjee (1992) and Bikhchandani et al. (1992). Angeletos et al. (2010) provide a related model applied to macroeconomic fluctuations.

[10] See De Long et al. (1990) and Shleifer and Vishny (1997).

[11] See for example models of categorical thinking (Mullainathan 2002), trend chasing (Hong and Stein 1999) and predictor selection dynamics (Brock and Hommes 1998).

[12] See, for example, Shiller (1981), Bondt and Thaler (1985), Lakonishok et alt. (1994), Jegadeesh and Titman (2001), and Baytas and Cakici (1999). For a comprehensive evaluation of these anomalies see Asness et al. (2013).

[13] Baker and Wurgler (2007), Jansen and Nahuis (2003) and Schmeling (2009).

There is a growing set of contributions that use information in the press to describe dynamics in macroeconomic and financial settings. Information in the press has been used to describe predictive content related to the economic cycle (Baker et al. 2012, Aromí 2014), to exchange rate volatility (Krol 2014) and to describe dynamics of consumer confidence (Doms and Morin 2004). Anticipation of daily stock market returns has been shown by Tetlock (2007) and Garcia (2013) for the US and Aromí (2013) for the case of Argentina. As in the case of the current study, but at higher frequencies, the evidence found in those articles is consistent with overreactions in stock prices.

The rest of the paper is organized as follows. Section II describes the data used in the study and the way in which media information is summarized. Section III presents the evidence from portfolio strategies. Investment strategies based on alternative sources of information are described in section IV. Section V presents evidence using monthly returns data. Section VI concludes.

II. Data and opinion metrics

The analysis uses two categories of yearly frequency information: financial assets returns and media content. The first set of data is given by the returns of stock market indices expressed in dollars. The main source for this data is the World Bank.[14] The data covers 34 countries over 26 years (1988-2013). For the early part of the sample (1988-1995), for some countries, this data was not available from this source. As a result, supplementary data was obtained from a private data vendor[15] and, in few cases, from the relevant stock exchange. The sample covers countries that belong to different regions and display heterogeneous levels of economic development.

Given the value of the stock market index of country i at the end of year t (SMI_{it}), the annual return in year t for country i is given by the difference of the logs of the index for years t and $t-1$: $r_{it} = \log(SMI_{it}) - \log(SMI_{it-1})$. Table 1 shows descriptive statistics for the return in the sampled countries.

The second type of data is an indicator of conventional views based on content published in the economic press. More specifically, this indicator was built based in information published in *The Wall Street Journal* (1984-2013) and *The Economist* (1992-2013). Together with *The Financial Times*, these publications are among the three main business publications in the English language.

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[14] http://data.worldbank.org/indicator/CM.MKT.INDX.ZG.

[15] http://www.tradingeconomics.com/

Table 1. Descriptive statistics

Country	Sentiment Index				Annual Return			
	Mean	St. dev.	Min.	Max.	Mean	St. dev.	Min.	Max.
Argentina	0.067	0.008	0.047	0.082	0.076	0.541	-0.821	1.617
Austria	0.052	0.007	0.039	0.067	0.027	0.325	-1.050	0.476
Belgium	0.059	0.006	0.048	0.071	0.046	0.316	-1.079	0.495
Brazil	0.062	0.005	0.051	0.072	0.091	0.628	-1.309	1.356
Chile	0.061	0.009	0.049	0.085	0.117	0.304	-0.528	0.668
Colombia	0.083	0.011	0.065	0.114	0.085	0.380	-0.635	0.765
Czech Republic	0.053	0.010	0.038	0.085	0.046	0.291	-0.616	0.565
Denmark	0.050	0.008	0.032	0.064	0.090	0.257	-0.713	0.445
Finland	0.050	0.007	0.034	0.060	0.075	0.391	-0.844	0.871
Greece	0.068	0.010	0.051	0.089	0.060	0.499	-1.079	1.092
Hungary	0.060	0.011	0.042	0.086	0.077	0.382	-0.994	0.693
India	0.069	0.008	0.053	0.088	0.077	0.372	-1.022	0.663
Indonesia	0.065	0.013	0.046	0.086	0.065	0.571	-1.347	1.261
Ireland	0.061	0.008	0.046	0.084	0.060	0.339	-1.204	0.438
South Korea	0.062	0.005	0.054	0.073	0.077	0.490	-1.171	0.793
Malaysia	0.058	0.011	0.038	0.077	0.060	0.374	-1.309	0.621
Mexico	0.064	0.008	0.053	0.081	0.149	0.363	-0.598	0.775
New Zealand	0.051	0.005	0.044	0.061	0.023	0.279	-0.734	0.470
Norway	0.055	0.007	0.044	0.074	0.056	0.343	-1.079	0.647
Pakistan	0.088	0.008	0.070	0.105	0.071	0.425	-0.968	0.751
Peru	0.072	0.012	0.047	0.102	0.201	0.423	-0.528	1.078
Philippines	0.070	0.008	0.055	0.087	0.060	0.450	-0.968	0.859

Table 1. (continued) Descriptive statistics

Country	Sentiment Index				Annual Return			
	Mean	St. dev.	Min.	Max.	Mean	St. dev.	Min.	Max.
Poland	0.063	0.008	0.053	0.090	0.109	0.583	-0.868	2.202
Portugal	0.059	0.011	0.043	0.078	0.025	0.278	-0.755	0.399
Russia	0.071	0.006	0.058	0.084	0.130	0.765	-1.833	1.345
Singapore	0.052	0.008	0.040	0.068	0.061	0.324	-0.755	0.571
South Africa	0.071	0.010	0.056	0.090	0.075	0.264	-0.545	0.445
Spain	0.058	0.008	0.045	0.077	0.065	0.246	-0.562	0.438
Sweden	0.053	0.006	0.043	0.069	0.083	0.312	-0.755	0.536
Taiwan	0.058	0.004	0.048	0.066	-0.012	0.352	-0.821	0.610
Thailand	0.068	0.011	0.047	0.097	0.044	0.527	-1.561	0.904
Turkey	0.073	0.007	0.060	0.086	0.055	0.618	-0.968	1.267
Venezuela	0.068	0.012	0.041	0.095	-0.014	0.500	-1.079	0.779
Vietnam	0.083	0.008	0.061	0.099	-0.105	0.503	-1.139	0.385
Average	0.063	0.008	0.048	0.082	0.065	0.412	-0.948	0.802

Note: The Sentiment Index was constructed using content from *The Wall Street Journal* (1984-2013) and *The Economist* (1992-2013). Annual Return is the dollar return of each country stock market index and was provided by the World Bank (1988-2013) and, in few instances, by tradingeconomics.com.

As discussed in the introduction, there are reasons to believe that conventional views can be approximated through content published in the media. On the other hand, summarizing media content to generate sentiment indices is a challenging task. Below a description of the path followed in this work is provided.

Opinions transmitted in the press regarding different countries are summarized computing the frequency of words with negative content in a relevant subset of text. This is a simple approach that has proven successful in other contexts.[16]

The first step in the construction of the indices involves identifying a list of keywords associated to each country: name of country, capital city[17] and demonym. Next, for each year in the sample period, the set of articles in which at least one of these keywords is present is identified. For each of these articles, the portions of text that are sufficiently close to a keyword associated to any country are selected. More specifically, the selection corresponds to words that are up to 10 words before or 10 words after one of the keywords associated to any country.[18] The strings of text associated to country c and year t are merged forming a selection of text K_{ct}. This concludes the text extraction stage.

An indicator of sentiment for the relevant country for each year is generated computing the frequencies of words with negative content. Following the seminal contribution by Tetlock (2007), the list of negative words is built using the negative valence category from the Harvard IV dictionary. The dictionary was procured from General Inquirer, a website that provides tools for content analysis of textual data.[19]

It must be noted that there are other lists of negative words that can be used in this analysis. In a relevant antecedent, Loughran and McDonald (2011) develop a list of negative words for financial contexts. Their analysis shows that informational gains can be attained using a more precise list of words. On the other hand, lists of words that are generated after the date of the sample run the risk of incorporating forward looking bias. As a result, despite the potential gains that could result from

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[16] In line with the findings reported in Tetlock (2007), indices constructed using words with positive content lack information on future stock returns. This can be explained by asymmetries in the information content of positive and negative words as found in the natural language processing literature (Garcia et al. 2012).

[17] In the case of Brazil, Spain, India, Philippines and South Africa big cities that can be unambiguously linked to the country are also included (e.g., Cape Town for South Africa).

[18] Following usual practice in content analyses, stop words (common words with no relevant content) were eliminated before neighboring text was extracted. Additionally, it is worth noting that variations in which 5 or 50 neighboring words were selected lead to very similar results.

[19] http://www.wjh.harvard.edu/~inquirer/homecat.htm.

considering alternative list of words, in the main part of the analysis we select the most cautious path and use the list originally employed in Tetlock (2007). Alternative lists are also evaluated as part of the sensitivity analysis.

The original list of negative words from General Inquirer includes 2291 words. In order to improve the precision of the indices, this original list was expanded to include plural noun forms, different verb tenses and adverbs. This procedure resulted in a list of 5364 words.

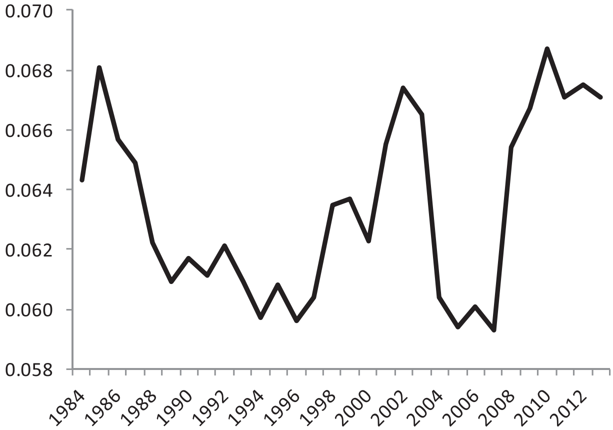
Let T_{ct} be the number of words in K_{ct}, the selected text corresponding to year t and country c and let N_{ct} be the number of times a negative word is detected in K_{ct}. Then, the corresponding sentiment index is given by $s_{ct} = N_{ct} / T_{ct}$. A higher number is associated to more pessimistic views while a lower number is associated to more optimistic assessments. Thus, the indicator could be labeled as a negative sentiment index. Throughout the document, at the risk of some confusion, the shorter expression sentiment index will be used. The construction of this indicator involves the selection of text comprising approximately 23 million words out of which more than 1.5 million correspond to words classified as negative words.

Table 1 shows important cross-country differences in the level of the sentiment index. The average value of the sentiment index ranges from 0.05 in the case of Denmark to 0.088 for the case of Pakistan. The standard deviation ranges from 0.004 in the case of Taiwan to 0.013 in the case of Indonesia. Looking more meticulously, it is found that the minimum value for the index is 0.032 and corresponds to Denmark in 1989. On the other hand, the maximum value is 0.114 and corresponds to Colombia during 2003, a year in which the country experienced weak economic performance and high levels of violence. These observations constitute a first indication suggesting that the index is able to capture important economic developments in the selected countries.

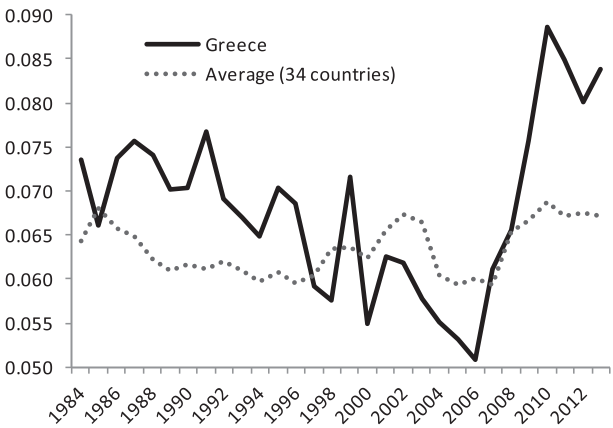
As a first step in the analysis, it could be instructive to observe the evolution of the indices during the sample period. Figure 1.A presents the average value of sentiment index for the 34 countries from 1984 through 2013. The path of the index suggests that there is a close association with the evolution of the global economy. For example, by a small margin, the minimum value is observed in 2007, on the final year of a period known as the great moderation. On the other hand, the maximum value is observed in 2010, in the aftermath of the global crisis originated in the U.S. and during a critical phase of the European crisis. In addition, a peak observed in 2001-2003 can be linked to the burst of the dot-com bubble, crises in emergent markets and the conflicts after 9/11. A period of low values is observed in the mid-nineties, a period of average economic bonanza.

Figure 1. Sentiment index

A. Average for 34 countries



B. Greece



Note: Shaded regions in panel A correspond to years with world GDP growth below 2%.

Additional preliminary insights can be gained considering the case of a single country. Figure 1.B shows the sentiment index for Greece. Particularly suggestive is the drop in the index, that is, the increasingly optimistic views observed from 2002 through 2006. In 2006 the index for Greece reaches a historic low of 0.0508. Four years after, in 2010, the index reaches a historic high of 0.0887. This extreme pattern is suggestive of overreaction in at least one of these instances. These observations based on anecdotal evidence are informative and suggests the plausibility of the overreaction conjecture. Formal empirical evaluations of this conjecture are implemented in the next sections.

III. Performance of contrarian portfolio strategies

In this section, contrarian portfolio strategies are implemented and their performance is evaluated. Each year, past values of the sentiment index are used to construct a portfolio of countries associated to past optimistic views and a portfolio of countries associated to past pessimistic views. Under the overreaction conjecture, it is expected that the first portfolio will experience inferior returns and the second portfolio will experience superior returns.

The sorting of countries is implemented using the average value of the sentiment index computed using four-year moving windows. It is expected that averaging the value of the index over multiple years will reduce noise in the identification of extreme views. Additionally, averaging is compatible with the focus of this study on low frequency, highly persistent dynamics.

A. Baseline estimates

As shown in the previous section, the mean values of the indices associated to different countries show ample variation. Hence, unless some correction is implemented, there are some countries that could be systematically associated to optimistic states or pessimistic states simply due to stable high or low values in the sentiment index. This suggests that adjusting for differences in mean values is needed if the intention is to capture changes in shared views about countries' prospects instead of reflecting countries' permanent characteristics. The indices are adjusted using the historical values of the index for the corresponding country.

Additionally, the indices associated to different countries express ample variation in terms of standard deviation. This could be due to more volatile perspectives or to differences in noise of the index due to heterogeneous levels of coverage of sampled countries. Taking into account these differences, in the exercise below the indices are adjusted using only historical information so any look-ahead bias is avoided.

More specifically, the standardized sentiment index $\hat{s}_{ct}$ is given by $\hat{s}_{ct} = \left(s_{ct} - \overline{s}_{ct}\right) / s_{ct}^{v}$ where $\overline{s}_{ct}$ is a weighted average of past values and s_{ct}^{v} is a measure of past volatility. Adjustment parameters are given by $\overline{s}_{ct} = \sum_{k=t_0}^{t-1} s_{ck}\,\omega(t-k)$ and $s_{ct}^{v} = \sum_{k=t_0}^{t-1} \left|s_{ck} - \overline{s}_{ck}\right| \omega(t-k)$, where t_0 is the first period of the sample and the weighting function $\omega(t-k)$ is a decreasing function which satisfies $\sum_{k=t_0}^{t-1}\omega(t-k)=1$, where $\omega(t+1)=(3/2)\omega(t)$, that is, the weight decreases with distance at a constant 33% rate. The weighting function captures the idea that more recent observations are more informative while the expanding window allows for more informed adjustments.[20] To secure for informed adjustment of the index value, the analysis is restricted to observations for which there exist at least four years of historic sentiment data. Finally, the indicator used to construct the portfolios for year t is the average value of the standardized index in the four most recent years $s_{ct}^{*}=\sum_{k=t-3}^{t}\hat{s}_{ck}$.

For each year, two portfolios are built identifying the top and bottom deciles using the adjusted index s_{ct}^{*}. The portfolio associated to optimism, or Portfolio 1, is composed by the stock market indices of the countries that belong to the bottom decile. Similarly, the portfolio associated to pessimism, or Portfolio 2, is composed by the stock market indices of the countries that belong to the top decile. Let $r_t^{P1(t-l)}$ be the average return in year t for the stock indices that belong to Portfolio 1 built in year $t-l$. In the same fashion, $r_t^{P2(t-l)}$ is the equivalent indicator for Portfolio 2. The analysis below will focus on the returns of these portfolios for different values of the lag parameter l. If extreme assessments are associated to excessive reactions, it is expected that Portfolio 1, the optimistic portfolio, will underperform and Portfolio 2, the pessimistic portfolio, will show superior performance.

In addition to comparing average returns, in this section a formal test for abnormal returns is implemented. A simple empirical model that includes a market factor is proposed. The statistical model is given by the following equation:

$$r_t^{P(t-l)}=\alpha+\beta r_t^{m}+\epsilon_t,$$

where $r_t^{P(t-l)}$ is the return of portfolio $P(t-l)\in\{P1(t-l),P2(t-l)\}$ in year t, r_t^{m} is the average return for all sampled countries in year t and ϵ_t is an error term. Following a standard procedure in the asset pricing literature, the estimate for the parameter α is interpreted as the abnormal return of the relevant portfolio. Additionally, similar calculations are computed for a long-short portfolio strategy in which Portfolio 1, the optimistic portfolio, is the short position and Portfolio 2, the pessimistic portfolio, is the long position. Standard errors and associated t-statistics are corrected for heterocedasticity.[21]

[20] Unreported exercises show that the results are not sensitive to changes in the weighting function.

[21] Package car in platform R was used to estimate robust standard errors.

Table 2. Performance of sentiment based portfolios

A. Return and performance for different lags in portfolio formation

Lags	Portfolio 1 (Optimism)				Portfolio 2 (Pesssism)				Portfolio 2 - Portfolio 1			
	Mean	St. Dev.	Alpha	t-stat.	Mean	St. Dev.	Alpha	t-stat.	Mean	St. Dev.	Alpha	t-stat.
0	0.087	0.302	0.038	0.9	0.121	0.435	0.049	0.9	0.034	0.337	0.011	0.1
1	0.045	0.367	-0.035	-1.3	0.210	0.372	0.134	2.7	0.165	0.245	0.169	2.7
2	0.011	0.340	-0.055	-2.2	0.058	0.387	-0.011	-0.2	0.047	0.249	0.044	0.7
3	-0.002	0.297	-0.062	-2.2	0.074	0.401	-0.001	-0.0	0.077	0.298	0.061	0.8
4	-0.016	0.310	-0.079	-2.5	0.126	0.295	0.068	1.7	0.142	0.167	0.147	2.9
5	0.002	0.348	-0.067	-1.7	0.155	0.336	0.088	2.7	0.153	0.258	0.155	2.5
6	0.007	0.324	-0.040	-1.3	0.072	0.379	0.022	0.4	0.066	0.279	0.022	0.4

B. Return and performance of mean sentiment based-portfolios (1 through 5 lags)

	Portfolio 1	Portfolio 2	Portfolio 2 - Portfolio1
Mean	0.010	0.121	0.111
St. dev.	0.324	0.337	0.176
Alpha	-0.059	0.051	0.110
t-stat.	-2.7	1.8	2.5

Notes: Panel A: Portfolio 1 has equal sized long positions in the stock indices of the countries of the most optimistic decile. Portfolio 2 has equal sized long positions in the stock indices of the countries in the most pessimistic decile. For the model: $r_t^{P(t-l)} = \alpha + \beta r_t^m + \epsilon_t$ for $l = 0,1,\ldots,6$, alpha is the estimated constant, $r_t^{P(t-l)}$ is the return of the corresponding sentiment-based portfolio (Portfolio 1, Portfolio 2 or Portfolio 1 – Portfolio 2), r_t^m is the market return and ϵ_t is an error term. Panel B: mean sentiment-based portfolio corresponds to the average of the portfolios with 1 through 5 lags in portfolio formation year. The associated return is: $\bar{r}^{P(t)} = \sum_{l=1}^{5} r_t^{P(t-l)} / 5$. The t-statistics are corrected for heterocedasticity.

Table 2.A shows the results for multiple values of the lag parameter l. One notable feature is the poor performance of Portfolio 1. From two years and up to six years after portfolio formation, the mean return of this portfolio is below 1.1%. More dramatically, for the case of three and four year lags, the mean return is negative. Similar conclusions emerge from observing the estimation of the market factor model. For example, four years after portfolio formation, the estimated abnormal return is -7.9%.

On the other hand, the performance of Portfolio 2, the portfolio associated to pessimism, takes the opposite direction. For example, one year after portfolio formation, the mean return is 21%. High values are also observed for the mean returns four and five years after portfolio formation. The estimations of factor models provide similar results. The abnormal returns one, four and five years after portfolio formation are estimated to be above 6.8% and statistically different from zero. In contrast, two and three year lags result in estimated abnormal returns that are slightly negative but statistically null.

The last panel in Table 2.A describes the return associated to the long-short portfolio strategy. Lags of one, four and five years result in positive abnormal returns of at least 15%. These estimations are suggestive of overreactions that are gradually corrected years after the extreme opinions are identified. Lags of two, three and six years show positive but statistically insignificant abnormal returns. At this stage, it is not clear whether the differences in performance for different number of lags are simply noise or reflect a stable property of the return reversal process. Another interesting observation is that the results suggest a weak contemporaneous relationship between conventional views and stock index returns.

In terms of summarizing the results of this exercise, it is convenient to provide a description of the performance of the portfolio strategies when the returns associated to different values of the lag parameter l are combined. With this objective, the average return $\overline{r}^{P(t)} = \sum_{l=1}^{5} r_t^{P(t-l)} / 5$ is computed for portfolios $P(t-l) \in \{P1(t-l), P2(t-l)\}$. In other words, the new portfolios are built combining, with equal weights, the portfolios that exploit information with one through five lags. It is expected that this portfolio will allow for a more precise assessment of the association between lagged sentiment and return differentials.

As shown in Table 2.B, the mean return of Portfolio 1 is 1% while the mean return of Portfolio 2 is 12%. Suggesting that risk considerations are unlikely to provide a satisfactory explanation, the estimated standard deviations for each portfolio are very similar. The estimated abnormal returns are -5.9% for the case of Portfolio

1 and 5.1% in the case of Portfolio 2. The associated long-short portfolio strategy results in a highly statistically significant abnormal return equal to 11%.

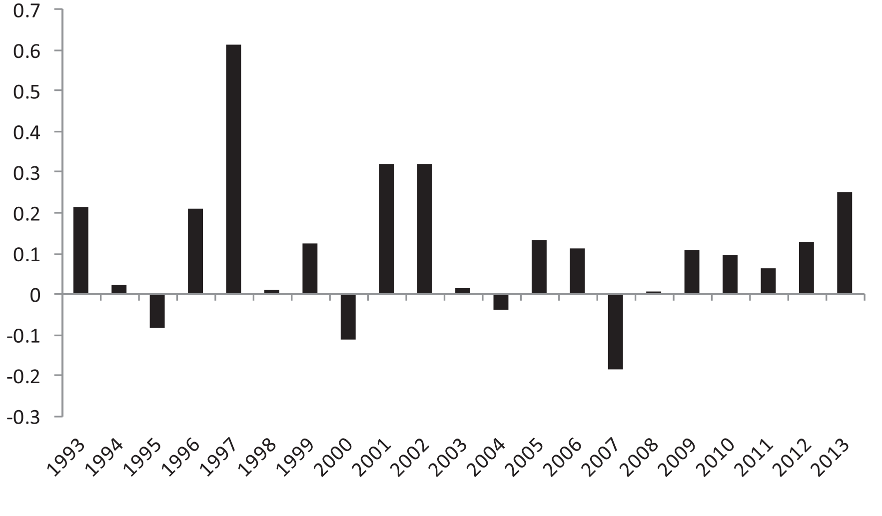
Figure 2 shows the returns of this long-short portfolio strategy. The figure shows a difference in performance that seems to be quite stable throughout the sample period. As can be observed, there are only four years in which the return is negative and in none of these years the return is below -20%. In contrast, the annual return is above 20% in six occasions.

The results presented above are consistent with the proposed conjecture of excessive responses associated to extreme opinions. Optimism is followed by underperformance and pessimism is followed by over-performance. This difference is highly persistent and stable over the sampled period. Risk considerations are unlikely to provide a satisfactory explanation.

B. Sensitivity analysis

In this subsection we provide information on several exercises in which aspects of the original exercise are modified. It is understood that this alternative exercises might shed light on the robustness of the previous results and the directions that

Figure 2. Returns of the long-short portfolio (based on four years of publications' data)



Notes: The bar corresponding to year t represents the average return on year t of the portfolios built using the sentiment indices of years t-5 through t-1.

can allow for informational gains. In general, the exercises show that the results are quite robust. Also, there seems to be little room for informational gains.

Table 3 provides information on the returns of the average contrarian portfolio under four types of modifications of the original exercise. The first analysis evaluates alternative sizes for the moving windows over which average sentiment is computed. As panel A shows, little changes are observed when the original size of 4 years is modified in the direction of shorter or longer periods.

The second examination deals with the selection of words. In the original exercises, words that are at a distance equal or lower than 10 from relevant keywords

Table 3. Characterization of returns in sensitivity analysis exercises

A. Size of moving window (years)

	3	4	5
Mean	0.110	0.111	0.119
St. dev.	0.177	0.176	0.172
Alpha	0.108	0.110	0.113
t-stat.	2.4	2.5	2.8

B. Maximum distance of selected words

	5	10	50
Mean	0.122	0.111	0.107
St. dev.	0.140	0.176	0.161
Alpha	0.122	0.110	0.112
t-stat.	3.0	2.5	2.6

C. Sentiment dictionary

	Harvard IV Dictionary	Loughran & McDonald (2011)	Mohammad & Turney (2013)
Mean	0.111	0.065	0.110
St. dev.	0.176	0.187	0.154
Alpha	0.110	0.063	0.112
t-stat.	2.5	1.3	2.5

D. Weight adjustment parameter

	1	1.5	2
Mean	0.110	0.111	0.092
St. dev.	0.175	0.176	0.165
Alpha	0.105	0.110	0.092
t-stat.	2.5	2.5	2.1

Notes: Return of the mean portfolios computed averaging the returns of the portfolios associated to 1 through 5 lags in formation year: $\bar{r}^{P(t)} = \sum_{l=1}^{5} r_t^{P(t-l)}$. Alpha is the estimated constant for the model: $r^{P(t)} = \alpha + \beta r_t^m + \epsilon_t$ for $l = 0,1,\ldots,6$. Where r_t^m is the market return and ϵ_t is an error term. t-statistics are corrected for heterocedasticity.

were selected. In the modified implementation presented in panel B of Table 3, distances of 5 and 50 are considered. It is verified that minor informational gains result from imposing a smaller distance. But the results are not significantly altered in any of the two cases.

Following Tetlock (2007), the sentiment indices were built exploiting the negative category in Harvard IV dictionary. Alternative lists of words could have been exploited. For example, Loughran and McDonald (2011) developed a list of negative words for financial contexts, while Mohammad and Turney (2013) constructed a dictionary of words employing a novel form of online collaboration. Panel C shows that our original exercise displays results that dominate those associated to the list of negative terms generated by Loughran and McDonald (2011) and are similar to the ones associated to the list generated by Mohammad and Turney (2013).

Finally, the standardization of individual country sentiment indices is considered. As described in the previous section, each country index was standardized using historic values of the average index and a historic metric of variability. In that exercise, the weight allocated to past values decreased with distance at a rate of 50% according to the rule: $\omega(t+1) = (3/2)\,\omega(t)$. In other words, the weight adjustment parameter was set equal to 3/2. According to the results shown in panel D, the results still hold when the rate at which the weight drops with distance is altered. It is observed that doubling the rate of increment in weights and keeping the weights constant result in similar properties for the distribution of returns of the contrarian sentiment long-short portfolio.

IV. Alternative sources of return prediction: past returns or economic growth

In this work, a novel source of persistent return predictability is identified. Extreme negative and positive opinions are found to predict expected returns. Shared views are computed using information distributed in the economic press. One relevant question is the extent to which similar return predictability could be achieved using more standard forms of information such as past returns or recent performance in terms of economic growth. This is a sensible consideration since periods of intense optimism are likely to be associated to positive returns and growth accelerations while periods of intense pessimism are commonly associated to negative returns and poor economic growth. Additionally, conventional opinions are measured with noise, hence it is plausible that alternative sources of information can result in more predictability.

In this section, two alternative sources of information are considered. A portfolio strategy that takes into account past economic growth is implemented. This portfolio strategy can be thought to evaluate the extent to which return predictability is explained by naïve projection of recent economic growth performance. Also, the case of portfolio strategies based on cumulative returns in the most recent years is considered. This strategy can be linked to the well-known literature that evaluates the performance of strategies that bet on previous losers and against previous winners.[22] In each case, the strategy is implemented following the algorithm described in the previous section.

Economic growth data from the World Bank is used to compute, for each year, the economic growth in the most recent four years.[23] Portfolio 1 is associated to the stock indices of countries in the decile with the largest economic growth. Portfolio 2 is the portfolio associated to the stock indices of countries in the decile with the lowest economic growth.

Similarly, in the case of strategies that exploit past returns, Portfolio 1 is associated to the stock indices that show the largest cumulative returns for the previous four years. Portfolio 2 is the portfolio associated to the stock indices with the lowest cumulative returns. The stock indices selected correspond to the top and bottom deciles respectively.

Table 4 describes the returns associated to the two portfolio strategies described above. For the strategy based on previous economic growth, the mean return associated to high growth is below the growth return associated to low economic

Table 4. Return and performance of alternative portfolio strategies

	GDP growth sorts			Past return sorts		
	High (H)	Low (L)	L-H	High (H).	Low (L)	L-H
Mean	0.024	0.079	0.055	0.019	0.074	0.055
St. dev.	0.404	0.385	0.353	0.345	0.408	0.252
Alpha	-0.052	0.009	0.061	-0.036	0.015	0.051
t-stat.	-1.1	0.2	0.7	-1.6	1.2	0.8
Correl. w/sentiment portfolio	0.53	0.66	0.71	0.75	0.57	0.70

Notes: Return of the mean portfolios computed averaging the returns of the portfolios associated to 1 through 5 lags in formation year : $\overline{r}^{P(t)} = \sum_{l=1}^{5} r_t^{P(t-l)}$. Alpha is the estimated constant for the model: $r^{P(t)} = \alpha + \beta r_t^m + \epsilon_t$ for $l = 0,1,\ldots,6$. Where r_t^m is the market return and ϵ_t is an error term. t-statistics are corrected for heterocedasticity.

[22] See Bondt and Thaler (1985) for the seminal contribution and Asness et al. (2013) for a recent comprehensive evaluation.

[23] The data is available at http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG.

growth. The estimated return is 6.1% when the market factor model is estimated. Nevertheless, the estimated parameter is not significantly different from zero. Despite the difference in terms of return predictability, it must be noted that there is a strong association between the return of the long short portfolio strategy based on extreme opinions and the return of the long short portfolio strategy based on economic growth. More precisely, the correlation coefficient for the returns of the respective long-short portfolios is 0.71.

Similar results are observed in the case of portfolio strategies that exploit information on past returns. The mean return for the portfolio of past winners is 1.9% while the mean return for past losers is 7.4%. The difference has the expected signed but is significantly smaller than the difference observed in the case of sentiment portfolios. According to the estimated market factor model the abnormal return is 5.1% but statistically it is not significantly different from zero. Despite the difference in performance, it is clear that the sentiment based strategy and the strategy based on past returns are strongly associated. The correlation coefficient for the returns of the long-short portfolios is 0.70.

In summary, it has been found that strategies based on past returns and economic growth are strongly linked to portfolio strategies based on sentiment indices. On the other hand, these alternative portfolio strategies are unable to replicate the performance of the sentiment based strategies. This suggests that the sentiment indices are able to reflect information on subjective states that cannot be captured with similar precision by alternative simpler indicators.

V. Performance of contrarian strategies at higher frequencies

So far the analysis has been carried out using annual returns data. This is consistent with the focus of this work on associations between data with multiple year lags. As shown in section III, sentiment indices are found to anticipate returns differentials up to five years after sentiment levels are measured. In favor of annual return data analyses, it must be noted that they exclude high frequency noise that might hide long term associations. In addition, comparable stock market data for long periods is more easily available at annual frequencies.

On the other hand, one shortcoming of low frequency analyses is given by the relatively small number of observations. Statistical tests are more reliable under a larger set of observations. Additionally, a monthly analysis can inform about the short term risk associated to exploiting this long term patterns in the data. In this section, the analysis of section III is replicated using monthly returns data.

As indicated, available data covers a shorter time span and a smaller set of countries. The sample period goes from January 1999 through July 2014. The number of sampled countries drops from 34 in the annual analysis to 30 in the monthly evaluation.[24] Dollar returns were computed using the stock index denominated in local currency and the dollar exchange rate for the last day of the month. The source for monthly stock market indices is Bloomberg. For most countries, exchange rate data corresponds to the daily series provided by the Federal Reserve Bank of St. Louis.[25] For eight countries, this data was not available from that source and was obtained from a private data provider.[26]

Table 5 shows results for the monthly frequency analysis. The average returns presented in panel A show that the returns following periods of high sentiment (high pessimism) are, on average, higher than the returns that follow periods of low sentiment (low pessimism). As in the annual analysis, the difference is the largest for five year lags. In this case, monthly average returns differ by 0.95%. This gap is similar to that observed in the annual returns analysis. The findings are also replicated when differences in volatility are evaluated. For example, portfolios built using five-year lagged sentiment metrics show no difference in terms of the standard deviation. In both cases, the standard deviation of monthly returns is approximately 7.4%. Importantly, despite the differences in data coverage and high frequency noise, the estimated abnormal returns and associated t-statistics are also in line with the annual return analyses.

Panel B in Table 5 shows the performance of the average portfolio strategy that combines portfolios built using one through five-year lagged indices. The monthly return of the portfolio associated to lagged optimism is 0.15%. In contrast, the monthly return of the portfolio associated to lagged pessimism is 0.96%. For the portfolio associated to optimism, the estimated monthly abnormal return is above 0.5% and highly significant in statistical terms. The third column shows that the average monthly return of a long-short portfolio strategy is 0.8%. The associated abnormal monthly return is 0.79% and statistically significant. This abnormal return is approximately 10% in annual terms which is similar to the value observed for a different sample in the annual frequency analysis of section III.

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[24] The list of countries 30 covered by the monthly returns dataset is given by: Argentina, Austria, Belgium, Brazil, Chile, Colombia, Denmark, Finland, Greece, India, Indonesia, Ireland, Malaysia, Mexico, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Taiwan, Thailand, Turkey and Vietnam.

[25] The series can be found at: https://research.stlouisfed.org/.

[26] The data from these countries (Argentina, Chile, Indonesia, Pakistan, Peru, Philippines, Turkey and Vietnam) was provided by OANDA (http://www.oanda.com/).

Table 5. Performance monthly of sentiment based portfolio strategies

A. Return and performance for different lags in portfolio formation

Lags	Portfolio 1 (Optimism)				Portfolio 2 (Pesssism)				Portfolio 2 - Portfolio 1			
	Mean	St. Dev.	Alpha	t-stat.	Mean	St. Dev.	Alpha	t-stat.	Mean	St. Dev.	Alpha	t-stat.
1	0.0015	0.0692	-0.005	-2.4	0.0108	0.0776	0.004	1.2	0.0093	0.0583	0.009	2.1
2	0.0012	0.0703	-0.006	-2.7	0.0079	0.0780	0.000	0.1	0.0067	0.0534	0.006	1.5
3	0.0012	0.0708	-0.006	-2.7	0.0080	0.0746	0.001	0.3	0.0068	0.0513	0.007	1.7
4	0.0005	0.0699	-0.007	-2.8	0.0081	0.0713	0.001	0.4	0.0076	0.0506	0.008	1.9
5	0.0033	0.0740	-0.004	-1.5	0.0128	0.0734	0.006	2.0	0.0095	0.0528	0.010	2.5
6	0.0050	0.0728	-0.002	-0.8	0.0110	0.0728	0.004	1.4	0.0060	0.0514	0.006	1.5

B. Return and performance of mean sentiment based-portfolios (1 through 5 lags)

	Portfolio 1	Portfolio 2	Portfolio 2 - Portfolio1
Mean	0.0015	0.0096	0.0080
St. dev.	0.0718	0.0770	0.0612
Alpha	-0.0056	0.0024	0.0079
t-stat.	-3.6	1.0	2.5

Notes: Panel A: Portfolio 1 has equal sized long positions in the stock indices of the countries of the most optimistic decile. Portfolio 2 has equal sized long positions in the stock indices of the countries in the most pessimistic decile. Alpha is the estimated constant for the model: $r_t^{P(t-l)} = \alpha + \beta r_t^m + \epsilon_t$ for $l = 0,1,\ldots,6$. Where, $r_t^{P(t-l)}$ is the return of the corresponding sentiment-based portfolio (Portfolio 1, Portfolio 2 or Portfolio 1 – Portfolio 2), r_t^m is the market return and ϵ_t is an error term. Panel B: mean sentiment-based portfolio corresponds to the average of the portfolios with 1 through 5 lags in portfolio formation year. The associated return is: $\overline{r}^{P(t)} = \sum_{l=1}^{5} r_t^{P(t-l)}$. t-statistics are corrected for heterocedasticity.

In summary, the analyses that use monthly return data are consistent with return predictability. Despite the high frequency noise that characterizes monthly returns and the reduced time and country sample coverage, the differences in return are statistically significant. The results serve as a robustness check of the exercises developed using annual return data.

VI. Conclusions

This study proposes a novel metric of conventional views to evaluate instances of overreaction in financial and macroeconomic contexts. More specifically, the metric uses content of the international economic press. The analysis focuses on the relative performance of stock market indices following periods of extreme opinions. The results show that strong positive views are associated to subsequent lower returns and strong negative views are associated to subsequent higher returns. The difference in returns is highly persistent; for example, returns for portfolios constructed using five year-old information show differences in means that are both statistically and economically significant.

The evidence is consistent with the occasional emergence of extreme shared views that result in mistaken valuations of a broad class of financial assets that are corrected in subsequent years. According to the results, predictable differences in risk cannot explain the differences in returns.

This evidence is relevant for the interpretation of dynamics in financial and macroeconomic contexts. The existence of recurrent, persistent and predictable overreactions has implications for both private actors' decision making and the design of public policies that aim for stability. Additionally, this evidence suggests that there is value in empirical analyses that exploit estimations of subjective states. Strategies based on past returns or economic growth records are not able to replicate the results attained when the sentiment indices are used.

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