Investor Sentiment and Economic Forces*

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Abstract

This study explores the role of investor sentiment in the pricing of a broad set of macro-related risk factors. Economic theory suggests that pervasive factors (such as market returns and consumption growth) should be priced in the cross-section of stock returns. However, when we form portfolios based directly on their exposure to macro-related factors, we find that portfolios with higher risk exposure do not earn higher returns. More important, we discover a striking two-regime pattern for all 10 macro-related factors: high-risk portfolios earn significantly higher returns than low-risk portfolios following low-sentiment periods, whereas the exact opposite occurs following high-sentiment periods. We argue that these findings are consistent with a setting in which market-wide sentiment is combined with short-sale impediments and sentiment-driven investors undermine the traditional risk-return tradeoff, especially during high-sentiment periods.

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1. Introduction

Economic theory (e.g., Merton's (1973) ICAPM) suggests that innovations in pervasive macro-related variables are risk factors that should be priced in the stock market. This study explores the pricing of macro factors in the cross section of stock returns. We construct portfolios by sorting individual stocks directly on their sensitivity to a broad set of macro-related factors. This approach provides a natural way to produce portfolios with di erent exposure to underlying factors. Thus, we believe that these beta-sorted portfolios are particularly well suited for the study of the pricing of macro risk factors.

We consider a large set of macro-related factors: consumption growth, industrial production growth, total factor productivity (TFP) growth, innovations in in ation, changes in expected in ation, the term premium, the default premium, the innovation in aggregate market volatility, aggregate market excess returns, and labor income growth. For each risk factor, we ex2line the strategy that goes long the stocks in the highest-risk decile and short those in the lowest-risk decile. Overall, we nd that the spread between high- and low-risk portfolios is close to zero (0.03% per month) and insigni cant, lending no support standard economic theory.[1]

Using the market-wide sentiment index constructed by Baker and Wurgler (2006), we explore sentiment-related mispricing as at least a partial explanation for the apparent empirical failure of economic theory. Whether investor sentiment a ects stock prices has been a question of long-standing interest to economists. In standard economic models, investor sentiment does not play a role in asset prices. Researchers in behavioral nance, in contrast, suggest that when arbitrage is limited, noise trader sentiment can persist in nancial markets and a ect asset prices (e.g., Delong, Shleifer, Summers, and Waldmann (1990) and Shleifer and Vishny (1997)).

Speci cally, following Stambaugh, Yu, and Yuan (2011), we investigate the hypotheses that result from combining two prolinent concepts in the literature. The rst concept is that investor sentiment contains a time-varying market-wide component that could a ect prices on many securities in the same direction at the same time.[2] The second concept is that

[1] One might argue that there are a lot of noises in beta estimations. Thus, it is not very surprising that return spreads between high- and low-risk rms are not signi cant. We are very sympathetic to this measurement error view. However, as we discuss in more detail later, our main results on the two-regime pattern are not subject to this criticism. Actually, potential measurement errors should weaken the two-regime pattern we document below.

[2] Studies addressing market-wide sentiment, among others, include Delong, et al. (1990), Lee, Shleifer, and Thaler (1991), Barberis, Shleifer, and Vishny (1998), Brown, and Cli (2004, 2005), Baker and Wurgler

impediments to short selling play a significant role in limiting the ability of rational traders to exploit overpricing.[3] Combining these two concepts, it follows that there are potentially many overpriced assets during high-sentiment periods. However, asset prices should be close to their fundamental value during low-sentiment periods, since underpricing can be counterveiled by arbitrageur, and pessimists tend to stay out of markets due to short-sale impediments. As a result, the market tends to be more rational and efficient during low-sentiment periods than during high-sentiment periods, and hence the first testable hypothesis regarding macro-related factors is that firms with high risk should earn higher returns than firms with low risk during low-sentiment periods.

Our second hypothesis is that during high-sentiment periods, the return spread between high- and low-risk portfolios should be smaller than that during low-sentiment periods and could potentially be negative. This hypothesis follows for at least two reasons. First, during high-sentiment periods, sentiment-driven investors tend to require a smaller compensation for the risk they bear, probably due to effectively lower risk aversion for the representative agent (see Yu and Yuan (2011)). Second, Hong and Sraer (2011) propose a model in which high market beta assets are endogenously more speculative due to their greater sensitivity to aggregate disagreement about the common cash flow factor. Extending their argument to general macro factors, one might conjecture that firms with high macro risk are more subject to the influence of market-wide sentiment (This conjecture is confirmed later in the data). Thus, high-risk firms are likely to be more overpriced than low-risk firms during high-sentiment periods. As a result, subsequent returns for high-risk firms could be lower than low-risk firms due to corrections to potential overpricing, despite higher systematic risk for high-risk firms.

Empirically, we find that all the beta-sorted portfolios have a positive return spread (0.61% per month on average) following low levels of sentiment (Hypothesis 1). We also find that the return spreads are significantly (1.17% per month) lower and negative (-0.56% per month) following high sentiment (Hypothesis 2). Moreover, we find evidence that high-risk portfolios earn lower returns following high investor sentiment, whereas low-risk portfolios

(2006, 2007, 2011), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), Frazzini and Lamont (2008), Kaniel, Saar, and Titman (2008), Livnat and Petrovic (2008), Antoniou, Doukas, and Subrahmanyam (2010), Gao, Yu, and Yuan (2010), Hwang (2011), Baker, Wurgler, and Yuan (2011), Yu and Yuan (2011), Stambaugh, Yu, and Yuan (2011), Chung, Hung, and Yeh (2011), and Yu (2013).

[3] Notable papers exploring the role of short-sale constraints in asset prices include Figlewski (1981), Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), Duffie, Garleanu and Pedersen (2002), Jones and Lamont (2002), Hong and Stein (2003), Scheinkman and Xiong (2003), Lamont and Stein (2004), Ofek, Richardson, and Whitelaw (2004), and Nagel (2005).

have similar returns following low and high sentiment, supporting our conjecture that high-risk firms are more influenced by sentiment. In addition, further time-series regressions confirm a significant negative relation between investor sentiment and the return spreads between high- and low-risk portfolios. Finally, our results are robust to macroeconomic effects as well as the use of the survey-based Michigan consumer sentiment index.

Despite an insignificant average price of risk for economic factors, our results suggest that during periods when the market participants are more rational, pervasive factors are indeed priced. We regard this finding as supportive to standard theory. During high sentiment periods, however, sentiment-induced mispricing appears to dominate, thereby causing high-risk firms to earn lower subsequent returns. As we discuss in more detail later, time-variation in risk premium or in risk aversion under a rational framework could potentially contribute to the two-regime pattern, as long as this time-variation is correlated with our sentiment measure. Given the negative return spread between high- and low-risk firms during high-sentiment periods, however, our evidence suggests that sentiment-induced mispricing should at least play a partial role in the patterns we have documented since a fully rational model with time-variation in risk premium would have difficulty to produce a negative risk-return relation.

In terms of the literature, this study builds on the earlier work of Baker and Wurgler (2006, 2007), who argue that market-wide sentiment should have a greater effect on securities that are hard to arbitrage and difficult to value. Using observable proxies for these two characteristics, Baker and Wurgler (2006, 2007) demonstrate intriguing patterns in the cross section of returns across different sentiment states, which are consistent with the importance of those characteristics.

Our study is also related to Stambaugh, Yu, and Yuan (2011), which studies the effect of investor sentiment on anomalies. They find that anomalous return spreads are much more pronounced following **high sentiment** due to sentiment-induced overpricing. In a related setting, we examine the effect of investor sentiment on the pricing of macro risk factors, rather than on anomalies, and we argue that high-risk firms should earn higher returns than low-risk firms following **low sentiment** since macro-related factors should be correctly priced during such periods. Thus, our study focuses on the effect of sentiment on leading asset pricing models, whereas Stambaugh, Yu, and Yuan (2011) is silent in this aspect. Another related study is Yu and Yuan (2011), who show that there is a significant positive relation between the aggregate market's expected return and its conditional volatility during low-sentiment periods and a nearly flat relation during high-sentiment periods. We extend their investigation on the aggregate time-series risk-return tradeo by exploring the much richer cross-sectional risk-return tradeo for a large set of macro-related factors.[4]

Although our study shares a similar underlying setting with the above papers, our paper di ers from earlier studies by focusing on the e ect of sentiment on many leading asset pricing models simultaneously. Our ndings also have distinctive implications for leading asset pricing models of cross-sectional returns. For example, the evidence that high-risk rms earn lower returns than low-risk rms during high sentiment poses a major challenge to traditional full-rational asset pricing models. On the other hand, the nding that high-risk rms earn higher returns than low-risk rms following low sentiment lends support to the traditional models during periods when market participants are closer to rational. Lastly, we view sharing a similar setting with existing studies as an advantage of our study, rather than a disadvantage. Using similar ingredients to account for a di erent set of asset pricing phenomena provides further validation on the importance of the sentiment channel in asset price movements and suggests that the sentiment e ect is pervasive, rather than an artifact of the data.[5]

Finally, this paper is also related to studies on the failure of the traditional CAPM model. Previous studies have suggested several forces responsible for the empirical failure of the CAPM, such as leverage aversion (Black (1972), Asness, Frazzini, and Pedersen (2012), and Frazzini and Pedersen (2011)), benchmarked institutional investors (Brennan (1993), Baker, Bradley, and Wurger (2011)), money illusion (Cohen, Polk, and Vuolteenaho (2005)), and disagreement (Hong and Sraer (2011)). We show that the sentiment e ect remains robust after controlling for these important economic forces.

The rest of the paper is organized as follows. In Section 2, we develop our hypotheses. Section 3 describes the investor sentiment data and discusses the underlying macro factors and the portfolios based on those factors. Section 4 reports the main empirical results. In Section 5, we investigate the robustness of our results and discuss alternative interpretations of our ndings. Section 6 concludes.

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[4]Pioneered by French, Schwert, and Stambaugh (1987), there is also a vast literature exploring the traditional risk-return tradeo under rational framework.

[5]Our approach is reminiscent of the studies on habit formation. Campbell and Cochrane (1999) show that external habit formation can help account for the equity premium puzzle, tle,r9(t)-hdiesren28(h)-40t

2. Hypotheses Development

As discussed in the introduction, the prices of risk for most macro-related factors are insignificant on average. In this section, we develop hypotheses that explore sentiment-induced mispricing as at least a partial explanation for this empirical finding. As in Stambaugh, Yu, and Yuan (2011), our hypothesized setting combines two prominent concepts: market-wide sentiment and short-sale impediments. However, rather than focus on asset-pricing anomalies as in their study, we focus on the resulting implications on the pricing of macro risk factors.

Many studies argue that the beliefs of many stock market investors share a common time-varying sentiment component that exerts market-wide effects on stock prices. Early studies typically focus on the effect of market-wide sentiment on aggregate stock returns. The evidence on the sentiment effect is not particularly strong. More recent studies borrow insights from advances in behavioral finance theory and provide much sharper tests for the sentiment effect on the cross-section of stock returns. Baker and Wurgler (2006), for example, discover that after higher market-wide sentiment, firms that are more subject to the influence of sentiment experience lower subsequent returns, whereas after lower market-wide sentiment, firms that are hard to value and arbitrage earn higher subsequent returns than firms that are easy to value and arbitrage.

Similar in spirit to Stambaugh, Yu, and Yuan (2011), combining market-wide sentiment with Miller's (1977) insight that stock prices reflect an optimistic view due to the effect of short-sale impediments leads to the implication that the stock market is more rational and efficient during low-sentiment periods.[6] During periods of high market-wide sentiment, the most optimistic views about many stocks tend to be overly optimistic, so many stocks tend to be overpriced. During low-sentiment periods, however, the most optimistic views about many stocks tend to be those of the rational investors, and thus mispricing during those periods is less likely.

Recently, Hong and Sraer (2011) propose a theoretical model in which assets with high market beta are endogenously more speculative due to their greater sensitivity to aggregate disagreement about the common cash flow factor. Due to short-sale impediments, firms with high market beta are likely to be more overpriced when aggregate disagreement, and

[6] Numerous studies have argued that there exist short-sale impediments in the stock market. These impediments include, but not limited to, institutional constraints, arbitrage risk (Pontiff (1996), Shleifer and Vishny (1997), and Wurgler and Zhuravskaya (2002)), behavioral biases of traders (Barber and Odean (2008)), and trading costs (D'Avolio (2002)).

hence market-wide sentiment, is large, leading to the failure of the CAPM. Extending their argument to a multi-factor setting where the underlying factors are the macro-related variables, we further conjecture that firms with high macro risk are more subject to the influence of market-wide sentiment. Consider the market factor as an example. If the stock market return is affected by investor sentiment, then high-beta firms are automatically more influenced by sentiment. More important, we empirically confirm this conjecture in the data. Combining the insights from Stambaugh, Yu, and Yuan (2011) and Baker and Wurgler (2006) with the above conjecture, we can reach our three testable hypotheses.

First, during low-sentiment periods, the market tends to be more rational, since pessimistic investors stay out of the market due to short-sale impediments and marginal investors tend to be rational. Thus, firms with high macro risk should earn higher subsequent returns due to the classic risk-return tradeoff. Second, it is plausible that low-sentiment periods coincide with periods with higher market risk premia. Thus, it is easier to identify a significant return spread during low-sentiment periods. Third, if firms with high macro risk are more subject to the influence of sentiment, the returns of firms with high macro risk should be higher following low-sentiment periods than firms with low macro risk due to sentiment-induced underpricing (see, e.g., Baker and Wurgler (2006)). These effects reinforce each other, and hence the return spread between high- and low-risk firms should be positive during low-sentiment periods. However, if underpricing is less prevalent, the last effect might be very weak in reality.

We examine 10 pervasive macro-related variables. If each of these variables is truly a priced risk factor in an efficient market, we then reach our first hypothesis.

Hypothesis 1: The return spread between high- and low-risk portfolios should be positive following low investor sentiment.

On the other hand, during high-sentiment periods, there are two opposing effects. First, as in the low-sentiment period, firms with high macro risk should earn higher returns due to the traditional risk-return tradeoff. However, this tradeoff is likely to be weaker during high-sentiment periods, since optimistic investors tend to demand lower compensation for bearing risk (see, e.g., Yu and Yuan (2011)).[7] Second, firms with high macro risk are likely to experience lower future returns, since these firms, which are typically more subject to the sentiment influence, are more overpriced than low-risk firms during high sentiment. Taken

[7] As we will discuss in more detail in Section 5.1., it is also conceivable that high-sentiment periods coincide with lower market risk premia. Thus, the return spread between high- and low-risk firms should be lower during high-sentiment periods.

together, the return spread between high and low macro risk firms should be smaller during high-sentiment periods than during low-sentiment periods. In addition, the return spreads could even be negative if the second effect dominates. This is especially true if the macro factor is not strongly priced (a weak first effect) or if the high macro risk firms are much more subject to the influence of investor sentiment than the firms with low macro risk (a strong second effect). Thus, we arrive at our second hypothesis.

Hypothesis 2: The return spread between high- and low-risk portfolios should be smaller and potentially negative following high investor sentiment.

Finally, since high-risk firms are conjectured to be more subject to the influence of investor sentiment, high-risk firms should be relatively more overpriced and earn lower returns following high sentiment than following low sentiment. On the other hand, firms with low risk are less subject to the effect of investor sentiment, and hence low-risk firms should earn similar returns following high and low investor sentiment. In sum, we arrive at our third hypothesis, which is a direct implication from the conjecture based on Hong and Sraer (2011).

Hypothesis 3: High-risk portfolios should have lower returns following high investor sentiment than following low sentiment, whereas low-risk portfolios should have similar returns following low and high sentiment.

One should not expect Hypothesis 3 to literally hold for all the beta-sorted portfolios. For example, if low-risk firms are also subject to, albeit to a lesser extent, the influence of investor sentiment, then high sentiment should forecast a lower subsequent return for low-risk firms as well.

It is worthwhile to emphasize that while our study shares a similar setting with Stambaugh et al. (2011), we focus on distinct implications. Stambaugh et al. (2011) examine the effect of sentiment on anomalies which should be more pronounced during *high-sentiment* periods, whereas our study focuses on risk factors, which should be more significantly priced during *low-sentiment* periods. Moreover, our analysis below can be viewed as an out-of-sample test of the same economic mechanism of combining short-sale impediments and market-wide sentiment. Showing supporting evidence in different applications makes us far more confident on the empirical relevance of this mechanism.

Finally, many fundamental mechanisms, including money illusion (Cohen, Polk, and Vuolteenaho (2005)) and the combination of divergence of opinions and short-sale constraints

(Miller (1977) and Hong and Sraer (2011)), can potentially lead to mispricing in the stock market. In the current study, we simply use investor sentiment of Baker and Wurgler (2006) as a proxy for mispricing, and we do not model or investigate possible underlying forces which lead to mispricing in the first place. Instead, we focus on the effect of stock market mispricing on the pricing of macro-related factors.

3. Data Description: Investor Sentiment and Macro Factors

3.1. Investor Sentiment

For our main analysis, we use the market-based sentiment measure constructed by Baker and Wurgler (2006) (hereafter, the BW sentiment index). The monthly BW sentiment index spans from July 1965 to December 2010. Baker and Wurgler (2006) form their composite sentiment index based on six individual sentiment proxies: the number of initial public offerings (IPOs), the average first-day returns of IPOs, the dividend premium, the closed-end fund discount, the New York Stock Exchange (NYSE) turnover, and the equity share in new issues. To purge the effects of macroeconomic conditions from their sentiment index, Baker and Wurgler (2006) first regress each of the individual proxies on six macroeconomic indicators: growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and a National Bureau of Economic Research (NBER) recession indicator. To further filter out idiosyncratic fluctuations in the six proxies and captures their common component, they take the first principal component of the six residual series from the regressions as their final composite index.

The BW sentiment index is plotted in Figure 1. It appears that the BW sentiment index lines up well with anecdotal accounts of fluctuations in sentiment, such as the so-called electronics bubble in 1968 and 1969, the biotech bubble in the early 1980s, and the internet bubble in the late 1990s. Finally, sentiment falls during the recent financial crisis and remains at a low level. Notice that sentiment is not extremely low during the recent financial crisis, which suggests that investors appear not to be excessively pessimistic during the financial crisis.

3.2. Macro-Related Factors

In addition to the macroeconomic variables originally studied by Chen, Roll, and Ross (1986), we explore a few new macro-related variables that are also likely to have pervasive effects on asset prices. These variables includes TFP growth, labor income growth, and aggregate market volatility. Below we briefly describe these macro-related factors.

In total, we consider 10 macroeconomic variables.

1: Consumption Growth

The seminal work of Lucas (1978) and Breeden (1979) shows that an asset should command a higher risk premium only if it covaries more with consumption growth. However, numerous studies find that the standard consumption-based CAPM tends to be rejected in cross-sectional tests. For example, Chen, Roll, and Ross (1986) find that consumption growth is not significantly priced by portfolios sorted by firm size. Following Chen, Roll, and Ross (1986), we choose monthly consumption growth (CON) as our consumption risk factor. Our results remain robust to quarterly consumption growth. The data on nondurables and services are obtained from the Bureau of Economic Analysis (BEA).

2 & 3: TFP Growth and Industrial Production Growth

Standard production-based asset-pricing models show that aggregate TFP growth should be positively priced. Firms with high exposure to aggregate TFP shocks should earn higher returns, since these firms perform badly during recessions (e.g., Jermann (1998), Gourio (2007), and Belo (2010)). We use both quarterly Solow residuals and monthly industrial production growth (IPG) as our measure of aggregate productivity shocks.[8]

4 & 5: Term Premium and Default Premium

When investment opportunities vary over time, the multifactor models of Merton (1973) and Ross (1976) show that risk premia are associated with the conditional covariances between asset returns and innovations in state variables that describe the time variation of the investment opportunities. It has been shown that both the term premium (TERM) and the default premium (DEF) are countercyclical and have predictive power for the stock market and the bond market. Thus, it is conceivable that these variables are pervasive macro variables and that they describe the changing investment opportunities in the sense

[8] Following Chen, Roll, and Ross (1986), we lead industrial production and TFP by one period since industrial production at month t actually is the flow of industrial production during month t.

of Merton's (1973) ICAPM. Here, the term premium is measured as the difference between the 20-year Treasury bond yield and the 1-year Treasury bond yield. The default premium is calculated as the difference between the BAA corporate bond yield and the AAA bond yield. Instead of estimating innovations in the term and default premia, we simply define the factors as the first difference of the corresponding raw variables. This approach allows us to avoid potential look-ahead biases and econometric mis-specifications.

6 & 7: Unexpected Inflation and Changes in Expected Inflation

Inflation is another pervasive factor, considered by Chen, Roll, and Ross (1986). They consider both unanticipated inflation (UI) and changes in expected inflation (DEI). We follow their approach in constructing these two factors. Specifically, let $I_t \equiv \log(CPI_t) - \log(CPI_{t-1})$, where CPI_t is the consumer price index at time t. Then, the unexpected inflation is defined as $UI_t = I_t - E_{t-1}(I_t)$, and changes in expected inflation are measured as $DEI_t = E_t(I_{t+1}) - E_{t-1}(I_t)$. Notice that the resulting unanticipated inflation variable, UI_t, is perfectly negatively correlated with the unanticipated change in the real interest rate. Thus, we do not consider the real rate as a macro factor in our study. Finally, following Fama and Gibbons (1984), the expected inflation is estimated by modeling the changes in inflation as an MA(1) process.

8: Aggregate Market Volatility

A growing recent literature examines the pricing of aggregate volatility risk.[9] Since increasing volatility typically represents a deterioration in investment opportunities, Campbell (1993, 1996) and Chen (2002) argue that investors want to hedge against changes in market volatility. In addition, periods of high volatility also tend to coincide with downward market movements (see, e.g., French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992)). As a result, assets that have high sensitivities to innovations in market volatility are attractive to risk-averse investors. The higher demand for stocks with high volatility betas increases their price and lowers their average return. In sum, economic theory suggests a negative price of risk for innovations in market volatility. Following French, Schwert, and Stambaugh (1987), we calculate monthly market volatility from daily stock returns, and changes in monthly volatility are used as the volatility factor.

9: Market Returns

[9] Among others, see, Coval and Shumway (2001), Ang, Hodrick, Xing, and Zhang (2006), Adrian and Rosenberg (2008), Bansal, Kiku, Shaliastovich, and Yaron (2011), and Campbell, Giglio, Polk, and Turley (2011).

Although the main focus of our study is to examine the relation between nonequity economic variables and stock returns, the market return is also a natural pervasive factor to consider given the prominence of CAPM (e.g., Sharpe (1964) and Lintner (1965)). Previous studies typically find that the market return is not significantly priced in the cross section of stock returns (see, e.g., Fama and French (1993)).[10] Many studies have suggested possible forces responsible for the empirical failure of the CAPM, such as leverage aversion (Black (1972), Asness, Frazzini, and Pedersen (2012), and Frazzini and Pedersen (2011)), benchmarked institutional investors (Brennan (1993), Baker, Bradley, and Wurger (2011)), money illusion (Cohen, Polk, and Vuolteenaho (2005)), and disagreement (Hong and Sraer (2011)). Here, we suggest another possible, but related, mechanism: the investor sentiment-induced overpricing.

10: Labor Income Growth

Following Fama and Schwert (1977), Campbell (1996) and Jagannathan and Wang (1996) argue that the human capital should be part of the market portfolio in the CAPM and labor income growth may proxy for the return on human capital. They find that labor income growth indeed has a significant and positive price of risk in cross-sectional tests of

Thus, there are many potential sets of testing portfolios. It is, sometimes, hard to interpret the evidence on the pricing of macro risk factors based on one particular set of testing portfolios. For example, investment-specific shocks are positively priced using 10 momentum portfolios as testing portfolios (Li (2011)), but negatively priced using 10 book-to-market portfolios as testing portfolios (Papanikolaou (2011)).[11]

Instead of relying on any specific firm characteristic to form testing portfolios, we utilize an alternative, yet complementary, approach in the literature. We construct portfolios by sorting individual stocks on their sensitivity to macro factors. This approach does not allow for the freedom in choosing testing portfolios and provides a natural way to produce spreads in exposure to risk factors for testing portfolios. Thus, these beta-sorted portfolios are particularly well suited for our study.

Before we form the beta-sorted portfolios, we briefly discuss the sign of the price of risk for macro-related factors. Economic theory strongly suggests that consumption growth, productivity shocks, labor income growth, and the market return factor should be positively priced in the cross section of stock returns, whereas aggregate volatility should have a negative price of risk. In addition, since both the term premium and the default premium tend to increase during recession (see Keim and Stambaugh (1986) and Fama and French (1989)), where the marginal utility tends to be high. We thus conjecture a negative sign for these two factors.[12] Finally, given that positive inflation innovation tends to occur during economic booms, we conjecture that the price of risk for inflation has a positive sign.[13]

For each of these macro factors in monthly (quarterly) frequency, at the beginning of each year we sort all firms from NYSE/AMES/NASDAQ (except the financial firms) into deciles based on their sensitivity to the underlying macro factor using the previous five-years (eight-years) of data. Here we follow Fama and French (1992) in choosing a five-year formation window for monthly factors. We also skip one period to ensure that all the data is available at portfolio formation. The portfolios are held for one year. We then calculate the monthly value-weighted portfolio returns within each decile of portfolios. Our results are similar if the portfolios are rebalanced quarterly. We order the portfolio such that portfolio 10 is always the one with the highest macro risk, while portfolio 1 is the safest portfolio. We

[11] There is a growing literature linking macroeconomic variables to asset-pricing anomalies. Lewellen, Nagel, and Shaken (2010) and Daniel and Titman (2012) provide an empirical assessment of this literature.

[12] Note that DEF and TERM predict both future returns and future volatility with the same positive sign. Thus, Merton's (1973) ICAPM is ambiguous about the sign of the price of risk for TERM and DEF (see, Maio and Santa-Clara (2012)).

[13] Indeed, the correlations of TERM and DEF to productivity and consumption shocks are all negative, while the correlations of UI and DEI to productivity and consumption shocks are all positive.

then construct a high-minus-low strategy using the extreme deciles, 1 and 10, with a long position in the high-risk decile and a short position in the low-risk decile.

In addition, we construct several combination/average portfolio strategies that take equal positions across individual portfolio strategies based on macro factors. The first combination strategy uses only portfolios based on consumption growth, TFP growth, industrial production growth, aggregate volatility, labor income growth, and market excess returns, since there is extremely strong economic intuition for the sign of the price of risk for these six factors. Because our prior on the sign of the price of risk for other factors is not as strong as the previous six variables, we gradually add the rest of factors into the combination portfolio strategies. As a result, our second combination strategy includes the term premium and the default premium in addition to the original six factors; the third combination strategy is the average across all 10 factors.

Table 2 reports summary statistics of monthly returns on the long-short strategies across all months in our sample period. Panel A indicates that the correlations among the high-minus-low portfolio returns are not particularly high. In addition, for the 10 individual high-minus-low portfolio returns, the percentages of overall variance explained by each of the first five principal components are $[0.40, 0.16, 0.09, 0.07, 0.06]$. Even the last principal component explains 3% of the variation. Given the low correlations between these underlying macro-related factors as shown in Table 1, it is not surprising that the correlations between return spreads are not particularly large.

Panel B of Table 2 shows that none of the 10 high-minus-low strategies produce significant positive average return spreads. The average return spread for the third combined strategy is an insignificant 3 basis points (bp) per month. In addition, many return spreads are actually negative. For example, the firms with high consumption risk earn a lower subsequent return than firms with low consumption risk. The biggest long-short return spread is based on industrial production growth, which is 39 bp per month and is statistically significant. Overall, the return spreads based on the sensitivity to underlying macro factors are typically insignificant, a result that is quite disappointing to leading economic models. These findings are not surprising. Existing evidence on the pricing of macro risk factor is relatively weak, probably due to measurement errors.

Panel C of Table 2 reports the ex post beta of the high-risk portfolio, the low-risk portfolio, and their difference. In general, the ex post beta spread is positive as expected. Many of the spreads are significant. Given the relatively low correlation between the stock market return and some of the macro factors, we view the positive ex post beta spread as reasonably big. More important, despite the marginally significant ex post beta spread, we still obtain a clear two-regime pattern in portfolio returns as we show below.

Frazzini and Pedersen (2011) show that leverage and margin constraints lead to the failure of CAPM and that assets with higher market beta earn lower risk-adjusted returns in various asset classes. Our results share a similar flavor: firms with higher beta with respect to various macro risk factors tend to have similar returns with the firms with lower beta. Thus, while Frazzini and Pedersen (2011) suggest betting against beta in various asset classes, our results suggest betting against various macro betas. In the next section, we go one step further by investigating the role of sentiment behind this result.

4. Main Empirical Analysis

Our empirical design is closely related to Stambaugh et al. (2011), by replacing their anomalies with our beta-sorted portfolios. Thus, the presentation of our empirical results closely follows their structure.

4.1. Average Returns across Two Sentiment Regimes

We first use the BW investor sentiment index to classify the entire period into high- and low-sentiment periods: a month is classified as high-sentiment (low-sentiment) if the sentiment level in the previous month is in the top (bottom) 50% of the entire sentiment series. We then compute average portfolio returns separately for these two regimes. Incidentally, out of the 84 months of NBER recession during our sample, 52 months are classified as high-sentiment, and only 32 months are classified as low-sentiment. Table 3 reports our main results.

Consider first Hypothesis 1, which predicts that the return spread between high- and low-risk portfolios should be positive following low sentiment. Table 3 reveals that each of the high-minus-low spreads exhibits positive average profits following low sentiment. At a 0.05 significance level, the (one-tailed) t-statistics for 6 of the 10 long-short portfolios reject the null hypothesis of no positive return spread following low sentiment. Here the one-tailed test is appropriate, since the alternative is a positive return spread. The average high-minus-low spread earns 61 bp per month following low sentiment, with a t-statistic equal to 3.00. This result is in sharp contrast to the insignificant overall return spreads in Table 2: the average spread between high- and low-risk firms is only 3 bp per month. Overall, the results in

Table 3 provide strong support for Hypothesis 1. This evidence suggests that the traditional economic theory works well, as long as the market participants are close to being rational. Thus, despite potential measurement errors in beta estimation, the findings in Table 3 lend support to standard economic theory.

Next consider Hypothesis 2, which predicts that average return spreads between high- and low-risk portfolios should be significantly lower (and potentially negative) following high sentiment than following low sentiment. The support for this hypothesis is also strong. In Table 3, return spreads between high- and low-risk firms are positive following low sentiment, whereas these spreads are significantly lower and negative following high sentiment (see the last three columns). Indeed, all of the spreads are consistently positive following low sentiment and consistently negative following high sentiment. In the last column, nine of them have t-statistics that reject the no-difference null in favor of Hypothesis 2 at a 0.05 significance level. The last average return spread between high- and low-risk portfolios is 117 bp higher per month (with t-statistic -4.05) following low sentiment than following high sentiment. In addition, the last average return spread is -56 bp per month following high sentiment with t-statistics -2.88. Similar results hold for the first and the second average portfolios. Again, these findings are in sharp contrast to the near zero unconditional return spreads in Table 2.

As discussed in the introduction, one might argue that the measurement errors in betas could lead to a low average return spread between high- and low-risk firms. We certainly do not rule out the potential role of measurement errors in the observed insignificant *average return spread* between high- and low-risk firms. However, since measurement errors in betas tend to reduce the true beta spread between high- and low-risk portfolios, it is more difficult to identify a positive return spread between high- and low-risk firms following low sentiment. In addition, taking this measurement error view to the extreme that the measured betas are pure noise, we should observe near zero return spreads between high- and low-risk firms following both high and low sentiment. Thus, the noises in beta estimation are likely to *weaken* the two-regime pattern we have documented above.

Finally, consider Hypothesis 3, which predicts that sentiment should exert a stronger effect on high-risk portfolios and a weaker or no effect on low-risk portfolios. Table 3 shows that high-risk portfolios earn lower returns following high sentiment, and all 10 factors have a t-statistic that rejects the no-difference null in favor of Hypothesis 3. Low-risk portfolios also tend to earn lower returns following high sentiment, but the magnitude is very small and none of the 10 factors is significant. For example, low-risk portfolios in the combination strategy earn 49 bp per month lower following high sentiment, but the t-statistic is only -0.95. Any evidence for sentiment effects on low-risk portfolios become even weaker after benchmark adjustment (as discussed below in Table 4). Overall, the evidence appears to be consistent with Hypothesis 3 as well.

A standard approach in the existing literature is to use the Fama-French three-factor model to adjust for risk compensation. If the Fama-French three-factor model can capture all of the risk, then there should be no Fama-French three-factor benchmark-adjusted return spread between high- and low-risk portfolios, even following low-sentiment periods. However, it seems unlikely that the Fama-French three-factor model captures all of the pervasive macro risk. Table 4 reports results for benchmark-adjusted excess returns. After benchmark adjustment, 5 of the 10 individual t-statistics reject the null in favor of Hypothesis 1, and the combined high-minus-low risk portfolio spread still earns 39 bp per month following low sentiment (t-statistic: 2.62). This evidence suggests that the Fama-French three-factor model does not capture all of the macro risk.

Adjusting for benchmark exposure does not affect the main conclusion from Table 3. For example, the average return spread between high- and low-risk portfolios is 97 bp higher per month (with t-statistic -4.32) following low sentiment than following high sentiment. Moreover, the benchmark-adjusted return on the low-risk portfolios in the combined strategy exhibits an insignificant and positive 8 bp difference between high- and low-sentiment periods. In Table 4, none of the t-statistics reject the no-difference null in favor of higher returns following low sentiment. In fact, 6 of the 10 differences go in the opposite direction. On the other hand, the benchmark-adjusted return on the high-risk firms in the combined strategy exhibits a significant and negative 89 bp difference between high- and low-sentiment periods. Thus, after controlling for the Fama-French three factors, the evidence is still consistent with the view that investor sentiment induces more mispricing in high-risk firms and induces little, if any, mispricing in low-risk firms.

It is worth noting that most of the low-risk portfolios earn close to zero benchmark-adjusted return following both high- and low-sentiment periods, suggesting that Fama-French three factors explain the cross-section of expected return among low-risk firms, which are not very sensitive the sentiment influence. However, all 10 high-risk portfolios earn negative benchmark-adjusted returns following high sentiment. The average benchmark-adjusted returns are significant negative (-0.57% per month with t-statistic 3.65), again suggesting overpricing for high-risk firms during high-sentiment periods. In contrast, 9 out of 10 high-risk portfolios earn positive benchmark-adjusted returns following low sentiment.

The average benchmark-adjusted returns are also significant and positive (0.33% per month with t-statistic 2.20), suggesting either that Fama-French three factors do not capture all the macro risk among high-risk firms, or underpricing for high-risk firms during low-sentiment periods.

Finally, one might argue that our two-regime results could be mechanical. If a variable (e.g., sentiment) can predict market excess returns, then automatically, the market price of risk for the market factor is lower following high sentiment than low sentiment. This is also consistent with the notation that sentiment captures time-variation in risk premia. However, the market excess return is still 0.25% per month following high sentiment. Thus, the market risk premium is still positive following high sentiment, albeit lower than that following low sentiment, which is 0.61% per month. Thus, our negative market price of risk following high sentiment is not a mechanical result. In the robustness checks section, we discuss the possibility that sentiment is a proxy for time-variation in risk aversion or risk premia in more detail.

Overall, the evidence in Tables 3 and 4 appears to support the traditional theory during low sentiment and suggests that market-wide sentiment creates overpricing, probably due to short-sale impediments, which in turn destroy the traditional risk-return tradeoff during high sentiment.

4.2. Predictive Regressions

In the previous subsection, we report the average portfolio returns within two sentiment regimes, where the regime classification is simply a dummy variable. In this subsection, we conduct an alternative analysis, using predictive regressions to investigate whether the level of the BW sentiment index predicts returns in ways that are consistent with our hypotheses. The regression approach allows us to easily control for other popular risk factors (e.g., the Fama-French three factors) and macro variables, which enables us to check that the sentiment effect we documented in the previous subsection is not just due to comovement with common factors. Table 5 reports the results of regressing excess returns on the lagged sentiment index.

Taken together, Hypotheses 1 and 2 predict a negative relation between the profitability of each high-minus-low risk portfolio spread and investor sentiment. Consistent with this prediction, the slope coefficients for the spreads based on all 10 factors are positive in Table 5. Eight of the individual t-statistics are significant at a one-tailed 0.05 significance level. The last combination strategy has a t-statistic of -4.26 in Table 5. Here, returns are measured in percentage per month, and the sentiment index is scaled to have a zero mean and unit standard deviation. Thus, for example, the slope coefficient of -0.55 for the combination strategy indicates that a one-standard-deviation increase in sentiment is associated with a 0.55% decrease per month in the long-short portfolio strategy.

Hypothesis 3 predicts a negative relation between the returns on the high-risk portfolio and the lagged sentiment level. Consistent with this prediction, the slope coefficients for the high-risk portfolios based on all 10 factors are negative. Moreover, all 10 individual t-statistics are highly significant. The last combination strategy has a t-statistic of -3.15. We see that a one-standard-deviation increase in sentiment is associated with a 1.07% lower monthly excess return on the high-risk portfolio. Hypothesis 3 also predicts a weaker relation between the returns on the low-risk portfolio and the lagged sentiment level. Consistent with this prediction, the slope coefficients for the low-risk portfolios based on all 10 factors are smaller in magnitude. For example, the last average strategy in Table 5 has a slope of -0.51, which is less than half of the magnitude for the average high-risk portfolio but is nevertheless significant.

Table 6 reports the results of regressing benchmark-adjusted returns on the lagged sentiment index. Incidentally, we find that after benchmark adjustment, there is no significant relation between returns on the low-risk portfolios and lagged sentiment. Here, we see that benchmark adjustment makes a noticeable difference. Without benchmark adjustment, the coefficients for the low-risk portfolio returns are all negative, and 6 of the 10 are significant at a 0.05 significance level for a one-tailed test (see Table 5). After adjusting for benchmark exposures, however, the results are largely in line with Hypothesis 3. In Table 6, 5 of the 10 low-risk portfolio slopes are insignificantly positive, and none of the five negative slopes is significant either. The average strategy has a tiny slope of -0.02 and a t-statistic of -0.26, thus confirming our conjecture that low-risk firms are much less sensitive to the influence of investor sentiment. On the other hand, the high-risk firms are still highly influenced by sentiment even after benchmark adjustment. Finally, the benchmark-adjusted return for the high-minus-low risk portfolio is harder to interpret based on our hypothesis due to the mixture of risk and mispricing. Nonetheless, for completeness we report the results for benchmark-adjusted long-short portfolios in the last two columns of Table 6.

Finally, we regress beta-sorted portfolio returns on contemporaneous sentiment changes. If the conjecture that high-risk firms are more subject to the influence of sentiment is true, we should observe a stronger comovement between returns on high-risk firms and sentiment changes. Indeed, Table 7 shows that the regression coefficient is larger for high-risk portfolios than for low-risk portfolios. This is true for all macro factors except DEI, for which the two-regime pattern is indeed slightly less evident (see Table 5 and 6).[14] Given this evidence, one might think that the higher return for high-risk firms might be due to the underpricing of these firms following low sentiment (e.g. Baker and Wurgler (2006)). However, we show in the next subsection that the underpricing effect seems to be much weaker than the overpricing effect. Thus, it is unlikely that sentiment-induced underpricing can account for all the positive return spread between high- and low-risk portfolios following low sentiment. Systematic risk seems a more plausible explanation for the positive return spreads during low-sentiment periods.

In sum, the predictive regressions in this subsection confirm the results from the simple comparisons of returns during high- and low-sentiment periods in the last subsection. Our evidence supports the view that sentiment-induced overpricing at least partially explains the insignificant average price of risk for the macro-related factors.[15]

4.3. Sentiment Change as a Factor: Implications on Asymmetric Mispricing

Although traditional economic theory allows no role for investor sentiment, Delong et al. (1990) and other subsequent studies argue that changes in sentiment itself present risk to arbitrageurs.[16] Thus, one might be interested in using sentiment itself as a risk factor. We repeat our analysis using sentiment as a factor. We find that firms with high exposure to sentiment changes earn higher returns following low sentiment, whereas the opposite is true following high sentiment. These findings are consistent with Baker and Wurgler (2006), who argue that firms that are more subject to the influence of sentiment (i.e., firms with high exposure to sentiment changes) should be more overpriced (underpriced) following high (low) sentiment. Baker and Wurgler (2006) use a few firm characteristics as proxies for the degree

[14] Interestingly, among all the beta-sorted portfolios, the low market beta portfolio has the lowest and close to zero exposure to sentiment, whereas the high market beta portfolio has the highest exposure to sentiment. This is probably due to the fact that market return itself is highly subject to the movement of sentiment, whereas other macro factors are less correlated with sentiment.

[15] Due to the small correlation between the predictive-regression residuals and the innovations in sentiment, the potential small-sample bias in predictive regressions, as studied by Stambaugh (1999), appears not to be a problem in the results reported here.

[16] Lee et al. (1991), for example, argue that noise traders' correlated trades create risk in the closed-end fund price above and beyond the riskiness of the underlying assets it holds. As a result, rational investors demand a risk premium for holding the fund, leading to closed-end fund discounts.

of sentiment influence. Instead of sorting on firm characteristics as in Baker and Wurgler (2006), however, one can form portfolios based directly on the sensitivity of firm returns to changes in sentiment. We take this complementary approach in Table 8.

In particular, the positive return spread following low-sentiment periods is consistent with both the concept of sentiment risk and the differential effect of the sentiment-induced mispricing across firms with different limits to arbitrage. In this study, we do not intend to distinguish these two alternative interpretations, since they might both be at play simultaneously. More important, the absolute magnitude of the spread following low sentiment is much lower than that following high sentiment (0.35% versus 1.21% per month). Moreover, part of the 35 bp could be due to the sentiment risk in the sense of Delong et al. (1990). Thus, the evidence seems to suggest that sentiment-induced overpricing is much more prevalent than sentiment-induced underpricing.

In addition, we repeat the regression analysis in Table 7 with sentiment-beta-sorted portfolios. As expected, the portfolio with low sentiment sensitivity has an insignificant regression coefficient of 0.33, while the portfolio with high sentiment sensitivity has a highly significant coefficient of 4.42. Thus, the high-minus-low portfolio has a coefficient of 4.08. With such a large exposure to sentiment, the high-minus-low portfolio based on sentiment changes has only a return spread of 0.35% per month following low sentiment. In contrast, Table 7 shows that although the average high-minus-low portfolio has a sentiment sensitivity coefficient of 1.17 (only about 1/4 of 4.08), the average return spread is 0.61% per month following low sentiment. Taken together, risk appears to be responsible for a large part of the observed positive return spread between high- and low-risk portfolios following low sentiment.

Another way to further confirm that sentiment-induced overpricing is more prevalent than underpricing is to use both the positive part and the negative part of sentiment to predict aggregate market returns. Panel C of Table 8 shows that the positive part of sentiment is a strong contrarian predictor for future aggregate market returns, whereas the negative part does not forecast market returns at all. In addition, the opposite sign obtains for the negative part. Thus, sentiment has predictive power only during high-sentiment periods, suggesting that sentiment-induced overpricing is more prevalent than sentiment-induced underpricing.

5. Robustness Checks

5.1. Interpretation Based on Time-Varying Risk Premia

One might argue that our findings could potentially be consistent with a risk-based explanation without resorting to irrational investor sentiment. In particular, if a higher risk premium on these risk factors or higher risk aversion coincides with periods with lower sentiment, part of our results could potentially obtain. For example, the high-minus-low return spread should be more positive following low sentiment. Many previous studies have documented that the market risk premium is countercyclical, and that variations in risk premia are typically correlated with business conditions (see, e.g., Keim and Stambaugh (1986) and Fama and French (1989)). Thus, it is worthwhile to repeat our previous analysis by controlling for business conditions.

In constructing their sentiment index, Baker and Wurgler (2006) have removed macro-related fluctuations by regressing raw sentiment measures on six macroeconomic variables: growth in industrial production; real growth in durable, nondurable, and services consumption; growth in employment; and an indicator for NBER recessions. We control for an additional set of five macro-related variables that have been shown to be correlated with risk premia and business conditions: the default premium, the term premium, the real interest rate, the inflation rate, and Lettau and Ludvigson's (2001) wealth-consumption ratio (CAY). This set of macro variables is also used as control in Stambaugh et al. (2011).

By regressing excess returns on the lagged sentiment index and the five lagged macro-related variables, we investigate whether the predictive ability of sentiment for subsequent returns is robust to including macro-related fluctuations in addition to those already controlled for by Baker and Wurgler (2006). The regression results, reported in Table 9, indicate that the effects of investor sentiment remain largely unchanged by including the additional five variables. In particular, the coefficients and their t-statistics are close to those in Table 5, in which the five additional macro-related variables are not included in the regressions.[17]

Overall, if time variation in the risk premium drives our results, it appears that this

[17] In untabulated results, we find that after benchmark adjustment, the returns on low-risk portfolios are not associated with lagged sentiment (coefficient = -0.02 and t-statistic = -0.35), whereas the returns on high-risk portfolios are significantly negatively associated with lagged sentiment (coefficient = -0.37 and t-statistic = -3.23), just as in Table 6.

variation is not strongly related to either the six macro variables controlled by Baker and Wurgler (2006) or the five additional variables included in our analysis. Of course, it could still be possible that the sentiment index itself captures time variation in risk, or risk aversion, which is not captured by the 11 macro variables. At the least level, we show that sentiment contains information regarding time variation in risk premia which is not captured by standard macro-related variables. More important, Yu and Yuan (2011) show that low-sentiment periods could be endogenously associated with periods of high effective risk aversion due to the limited market participation resulting from short-sale constraints or a convex demand function for stocks. Thus, it is theoretically feasible that sentiment can be related to effective risk aversion and hence the price of risk. In this broad sense, our sentiment-based interpretation is consistent with the time-varying risk aversion story.

Finally, as argued by Stambaugh, Yu, and Yuan (2012), investor sentiment could be related to macroeconomic conditions. It is quite possible that after favorable (adverse) macroeconomic shocks, some investors become too optimistic (pessimistic) and push stock prices above (below) levels justified by fundamental values. Thus, as long as high (low) sentiment makes overpricing (underpricing) more likely, the extent to which sentiment relates to the macroeconomy or risk aversion does not affect the implications explored in this study. For instance, even if there is a strong link between sentiment and risk aversion, there still remains the challenge of explaining, across all 10 macro-related factors, why high-risk firms earn lower returns following high sentiment. It appears that sentiment-induced mispricing, especially overpricing, is at least partially responsible for this empirical fact.

5.2. Alternative Sentiment Index

We also investigate the robustness of our results to using an alternative sentiment index: the University of Michigan Consumer Sentiment Index. Many previous studies regarding investor sentiment have used this index (e.g., Ludvigson (2004), Lemmon and Portniaguina (2006), and Bergman and Roychowdhury (2008)). While the BW sentiment index is a measure of sentiment based on stock market indicators, the Michigan sentiment index is a survey-based measure. The monthly survey is mailed to 500 random households and asks their views about both the current and expected business conditions. As a result, the Michigan sentiment index might be less tied to the sentiment of stock market participants. To remove the business cycle component from the index, we use the residuals from a regression of the Michigan index on the six macro variables used by Baker and Wurgler (2006).

Table 10 reports the results of regressing excess returns on the lagged Michigan sentiment index as well as on the lagged macro-related variables. Our three hypotheses are supported, with the Michigan index as a proxy for sentiment. For the average high-minus-low risk portfolio based on the 10 factors, the return spread is signi cantly lower following high sentiment than following low sentiment, and low-risk rms are not signi cantly a ected by market-wide sentiment. The patterns of the results across the 10 macro factors are also similar to those obtained using the BW index, as reported in Table 5, although some of the patterns are slightly weaker. The weaker results would also be expected if the BW index is a better measure of the mood of stock market participants.[18]

5.3. Spurious Regression Critique

Because investor sentiment indices are quite persistent, our predictive regressions are subject to the spurious regression critique of Ferson, Sarkissian, and Simin (2003). To address this concern, we perform a simple Monte Carlo simulation analysis.

We independently simulate autoregressive arti cial sentiment processes with the same persistence as the BW sentiment index. We then perform the same two-regime sentiment analysis as in Table 3 by using the simulated sentiment index. The corresponding t-statistics for the last column of Table 3 are collected. We repeat the above procedure for 1,000 times to obtain 1,000 by 13 t-statistics panel for the last column of Table 3. Panel A of Table 11 reports the 2.5%, 5%, 50%, 95%, and 97.5% quantiles of the t-statistics. It can be seen that the 2.5% quantiles are around -1.96. Thus, the spurious regression critique does not pose an issue for our analysis. We also perform the same analysis by using arti cial sentiment index as a continuous variable as in Table 5. These results, omitted for brevity and available upon request, remain similar.

Panel B of Table 11 reports the fraction of simulations with all 10 t-statistics for individual macro-related factor less than a certain value. In general, it is very rare to obtain the same sign in those 10 individual regressions. For the two-regime analysis, there are only 2.8% chances that all the 10 beta-sorted portfolio has a higher spread following low sentiment than high sentiment. Using sentiment as a continuous variable yield essentially the same results. For example, none of these 1,000 simulation produce t-statistics simultaneously less

[18] In untabulated analysis, we nd that our results in Table 10 become slightly stronger when d sig 0 G8(d)1(ulatet)-4

than -1 for all 10 factors.

In sum, the spurious regression critique does not pose a problem for our results. Furthermore, it is quite rare to obtain a consistent sign for all the 10 macro-related factors in the analysis performed in both Table 3 and 5.

5.4. Controlling for Alternative Mechanisms

As mentioned earlier, many studies have suggested possible forces responsible for the empirical failure of the CAPM, such as leverage aversion, money illusion, and disagreement. Although we consider a much broader set of factors, it is still conceivable that the mechanisms proposed by these studies also work for our broad set of macro-related factors. Moreover, it is certainly possible that the forces proposed by these studies overlaps with our sentiment-channel. For example, when aggregate disagreement is high, there might be more overpricing due to short-sale impediments. Indeed, the correlation between sentiment and aggregate disagreement is about 54%. Thus, it is interesting to investigate whether sentiment still has predictive power after controlling for these mechanisms.

To investigate this possibility, in the Table 12, we perform the regression analysis by controlling for the effect from funding constraints (TED) of Frazzini and Pedersen (2011), the money illusion effect (inflation) of Cohen, Polk, and Vuolteenaho (2005) and aggregate dispersion of Hong and Sraer (2011) and Yu (2011). As shown in Table 12, the significant predictive power of sentiment for the high-minus-low return spreads remains quantitatively similar. Thus, our mispricing channel provides incremental predictive power for the high-minus-low risk portfolio returns.

In addition, in untabulated analysis, we study several additional factors proposed by recent studies. These factors include the cash flow news and the discount rate news of Campbell and Vuolteenaho (2004) and the average correlation and the average volatility factors of Chen and Petkova (2012). Similar to the 10 factors studied in the paper, we find that for these additional factors, the average return spreads between high- and low-risk firms are insignificant and close to zero. In addition, these spreads are positive following low sentiment periods, and negative following high sentiment periods. The differences-in-differences are economically large and statistically significant. These results are available upon request.

Finally, notice that the BW sentiment index has a look-ahead bias due to the principal component analysis and orthogonalization, although the macro-related factors are observable in real time, Thus, in untabulated analysis, we form the sentiment index recursively in real time without the look-ahead bias, and we then repeat the analysis in Tables 3 and 8 with this new real-time sentiment index. These results, omitted for brevity and available upon request, remain quantitatively similar.

6. Conclusions

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Figure 1
The Investor Sentiment Index

The sentiment index spans from 1965:07 to 2010:12. It is constructed as the rst principal component of six sentiment proxies. The six individual proxies are the closed-end fund discount, the NYSE share turnover, the number and average of rst-day returns on IPOs, the equity share in new issues, and the dividend premium. To control for macro conditions, the six raw sentiment measures are regressed on the growth in industrial production, the growth in durable consumption, the growth in nondurable consumption, the growth in service consumption, the growth of employment, and a dummy variable for NBER recessions.

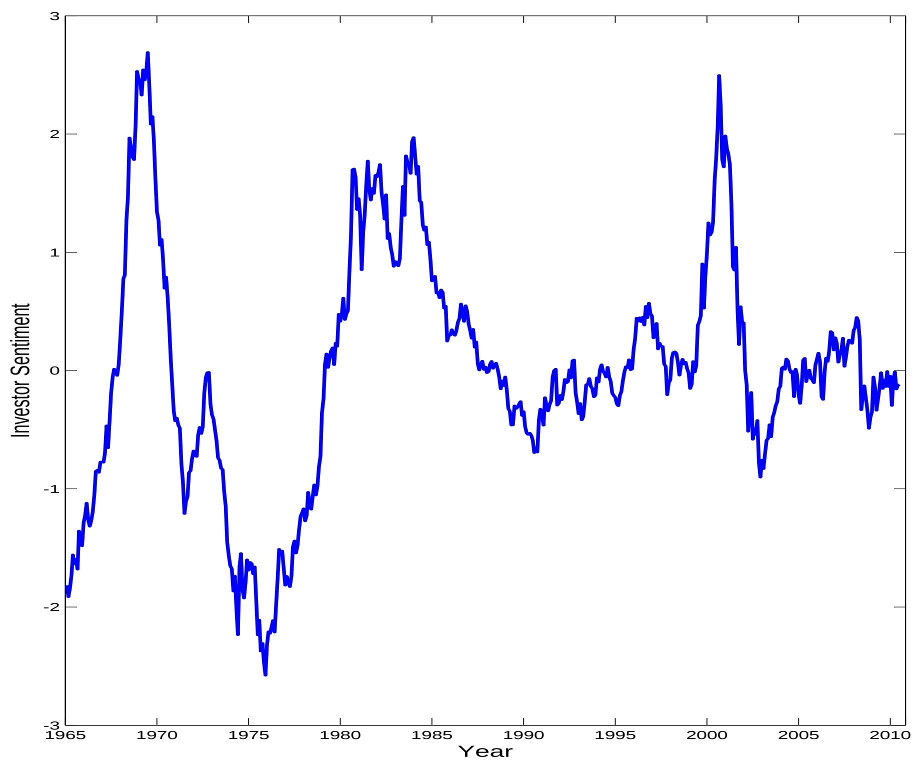

Table 1
Correlations among the Macro Factors

The table reports the correlations among macro factors, the correlations between the BW sentiment index and macro factors, and the autocorrelations of degree 1 to 8 of macro factors. TFP growth is sampled at a quarterly frequency, and the rest of variables are sampled at a monthly frequency. To calculate the correlations between factors, monthly factors are time-aggregated to quarterly frequency. Both levels and changes in sentiment are taken directly from Baker and Wurger's online dataset. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		A. Correlations among macro factors									
(1)	*CON*	1.00									
(2)	*TFP*	0.42	1.00								
(3)	*IPG*	0.52	0.32	1.00							
(4)	*TERM*	-0.27	-0.17	-0.20	1.00						
(5)	*DEF*	-0.16	-0.28	-0.28	0.19	1.00					
(6)	*UI*	0.07	0.15	0.16	-0.09	-0.27	1.00				
(7)	*DEI*	0.22	0.17	0.18	-0.11	-0.15	0.65	1.00			
(8)	*VOL*	-0.03	-0.03	0.05	0.00	0.03	0.03	0.11	1.00		
(9)	*MKT*	0.18	0.14	0.03	0.03	-0.05	-0.07	-0.14	-0.23	1.00	
(10)	*LAB*	0.36	0.16	0.16	-0.13	0.00	0.03	0.07	-0.00	0.06	1.00
		B. Correlation between macro factors and B-W sentiment (%)									
	S_{t-1}	-3.96	-9.68	-11.88	5.17	3.17	-6.13	-6.69	2.80	-7.02	-9.89
	S	22.05	17.30	4.58	-3.95	-9.22	16.04	11.23	-9.76	25.48	9.34

C. Autocorrelation among the macro factors

	1	2	3	4	5	6	7	8
CON	-0.132	0.097	0.211	-0.013	0.062	0.046	0.046	0.088
TFP	0.074	0.162	-0.071	-0.027	-0.119	-0.098	-0.066	-0.096
IPG	0.354	0.294	0.288	0.234	0.110	0.116	0.069	0.089
TERM	0.116	-0.021	-0.026	-0.076	-0.072.485 0 Td [(In6)-10.04(5.1a6)-1096(-0m505))]TJ/F11			

Table 2
Macro-Factor-Based Portfolio Returns across All Months

The table reports the correlation, the mean value, and t-statistics of beta-sorted portfolio returns across all months. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
							A. Correlations: High-minus-Low Risk Portfolios							
(1)	*CON*	1.00												
(2)	*TFP*	0.34	1.00											
(3)	*IPG*	0.36	0.14	1.00										
(4)	*TERM*	0.06	-0.02	0.23	1.00									
(5)	*DEF*	0.23	0.30	0.38	0.16	1.00								
(6)	*UI*	-0.10	-0.03	0.23	0.28	0.16	1.00							
(7)	*DEI*	-0.12	-0.04	0.20	0.21	0.21	0.55	1.00						
(8)	*VOL*	0.43	0.28	0.35	0.07	0.36	0.15	-0.04	1.00					
(9)	*MKT*	0.46	0.36	0.37	0.22	0.32	0.16	-0.02	0.66	1.00				
(10)	*LAB*	0.23	0.25	0.43	0.22	0.40	0.42	0.34	0.48	0.44	1.00			
(11)	*Ave*1	0.67	0.55	0.61	0.19	0.47	0.21	0.07	0.79	0.84	0.68	1.00		
(12)	*Ave*2	0.62	0.52	0.62	0.37	0.61	0.25	0.13	0.75	0.81	0.69	0.97	1.00	
(13)	*Ave*3	0.52	0.46	0.63	0.41	0.61	0.47	0.36	0.69	0.75	0.74	0.92	0.96	1.00
							B. Excess Returns							
							Means							
High Risk		0.29	0.75	0.79	0.52	0.40	0.52	0.46	0.49	0.45	0.16	0.49	0.48	0.48
Low Risk		0.46	0.38	0.41	0.32	0.54	0.52	0.52	0.35	0.49	0.60	0.45	0.44	0.46
High − Low		-0.17	0.36	0.39	0.20	-0.14	0.00	-0.06	0.15	-0.04	-0.44	0.04	0.04	0.03
							t-statistics							
High Risk		0.77	2.10	2.06	1.49	1.07	1.58	1.39	1.20	1.00	0.39	1.28	1.30	1.36
Low Risk		1.53	1.36	1.27	0.97	1.95	1.60	1.52	1.46	2.80	2.03	1.87	1.78	1.75
High − Low		-0.70	1.49	1.86	0.79	-0.53	0.00	-0.24	0.54	-0.10	-1.53	0.22	0.23	0.16
							C. Ex Post Betas							
							Point Estimates							
High Risk		3.91	4.59	0.59	4.55	-2.88	-0.87	-6.78	-1.36	1.77	1.13			
Low Risk		2.30	3.06	0.37	-5.20	-6.56	-2.55	-7.71	-2.90	0.61	0.32			
High − Low		1.61	1.52	0.22	9.75	3.68	1.68	0.93	1.54	1.17	0.81			
							t-statistics							
High Risk		4.48	3.43	1.23	0.46	-1.06	-0.45	-1.32	-3.49	25.27	1.52			
Low Risk		4.16	2.77	0.84	-0.43	-1.63	-1.32	-1.42	-5.59	13.42	0.59			
High − Low		2.32	1.85	0.96	1.42	1.68	1.83	0.43	4.99	10.89	1.90			

Table 3
Macro-Factor-Based Portfolio Returns during High and Low Sentiment

The table reports average portfolio returns in excess of the one-month T-bill rate in months following high- and low-sentiment regimes, as classi ed based on the median level of the BW sentiment index. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all macro-factor-based portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

	Low Risk			High Risk			High − Low		
	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low
CON	0.19	0.73	-0.54	-0.48	1.06	-1.54	-0.67	0.33	-1.00
	(0.39)	(2.15)	(-0.92)	(-0.85)	(2.26)	(-2.08)	(-1.77)	(1.12)	(-2.06)
TFP	0.21	0.56	-0.35	0.08	1.42	-1.34	-0.13	0.86	-0.99
	(0.46)	(1.67)	(-0.64)	(0.14)	(3.26)	(-1.88)	(-0.35)	(2.68)	(-1.97)
IPG	-0.08	0.89	-0.97	-0.11	1.70	-1.81	-0.03	0.80	-0.83
	(-0.16)	(2.18)	(-1.48)	(-0.18)	(3.87)	(-2.38)	(-0.09)	(2.99)	(-2.12)
TERM	0.10	0.54	-0.44	-0.23	1.26	-1.49	-0.33	0.72	-1.05
	(0.19)	(1.36)	(-0.68)	(-0.43)	(2.86)	(-2.12)	(-1.00)	(1.99)	(-2.17)
DEF	0.46	0.62	-0.16	-0.50	1.30	-1.81	-0.96	0.69	-1.64
	(1.08)	(1.78)	(-0.30)	(-0.91)	(2.66)	(-2.39)	(-2.91)	(1.89)	(-3.35)
UI	0.22	0.82	-0.60	-0.22	1.27	-1.49	-0.45	0.45	-0.89
	(0.45)	(1.88)	(-0.90)	(-0.45)	(2.99)	(-2.29)	(-1.36)	(1.47)	(-2.00)
DEI	0.09	0.94	-0.85	-0.35	1.27	-1.62	-0.45	0.33	-0.78
	(0.18)	(2.29)	(-1.23)	(-0.70)	(3.01)	(-2.44)	(-1.22)	(1.05)	(-1.61)
VOL	0.09	0.61	-0.51	-0.32	1.31	-1.63	-0.41	0.70	-1.11
	(0.23)	(2.36)	(-1.09)	(-0.52)	(2.51)	(-2.01)	(-1.13)	(1.84)	(-2.09)
MKT	0.57	0.41	0.16	-0.45	1.35	-1.80	-1.02	0.94	-1.96
	(2.31)	(1.76)	(0.50)	(-0.67)	(2.32)	(-2.02)	(-1.74)	(1.92)	(-2.56)
LAB	0.26	0.94	-0.68	-0.92	1.24	-2.15	-1.17	0.30	-1.47
	(0.58)	(2.55)	(-1.18)	(-1.46)	(2.55)	(-2.69)	(-2.83)	(0.83)	(-2.67)
*Ave*1	0.21	0.69	-0.48	-0.37	1.35	-1.71	-0.57	0.66	-1.23
	(0.55)	(2.36)	(-1.02)	(-0.63)	(2.91)	(-2.27)	(-2.10)	(2.76)	(-3.31)
*Ave*2	0.22	0.66	-0.44	-0.37	1.33	-1.70	-0.59	0.67	-1.26
	(0.57)	(2.20)	(-0.89)	(-0.65)	(2.93)	(-2.31)	(-2.60)	(3.06)	(-3.87)
*Ave*3	0.21	0.71	-0.49	-0.35	1.32	-1.67	-0.56	0.61	-1.17
	(0.52)	(2.21)	(-0.95)	(-0.65)	(2.98)	(-2.35)	(-2.88)	(3.00)	(-4.05)

Table 4

Benchmark-Adjusted Portfolio Returns during High and Low Sentiment

The table reports average benchmark-adjusted portfolio returns following high- and low-sentiment regimes, as classi ed based on the median level of the BW sentiment index. The average returns in high- and low-sentiment periods are estimates of a_H and a_L in the regression, $R_{i;t} = a_H d_{H;t} + a_L d_{L;t} + bMKT_t + cSMB_t + dHML_t + {}_{i;t};$ where $d_{H;t}$ and $d_{L;t}$ are dummy variables indicating high- and low-sentiment periods, and $R_{i;t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the di erence. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

	Low Risk			High Risk			High − Low		
	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low	High Sent.	Low Sent.	High −Low
CON	-0.01	-0.03	0.02	-0.73	-0.02	-0.71	-0.72	0.01	-0.73
	(-0.04)	(-0.16)	(0.05)	(-3.98)	(-0.09)	(-2.61)	(-1.99)	(0.03)	(-1.59)
TFP	0.08	-0.10	0.18	-0.14	0.46	-0.60	-0.22	0.57	-0.78
	(0.36)	(-0.61)	(0.65)	(-0.59)	(2.02)	(-1.85)	(-0.62)	(1.78)	(-1.63)
IPG	-0.23	0.06	-0.29	-0.31	0.72	-1.03	-0.08	0.66	-0.74
	(-1.08)	(0.37)	(-1.08)	(-1.21)	(2.77)	(-2.91)	(-0.29)	(2.40)	(-1.94)
TERM	-0.13	-0.37	0.23	-0.36	0.44	-0.80	-0.23	0.81	-1.04
	(-0.56)	(-1.72)	(0.74)	(-1.58)	(2.11)	(-2.55)	(-0.70)	(2.44)	(-2.24)
DEF	0.33	-0.10	0.43	-0.79	0.21	-1.00	-1.13	0.31	-1.43
	(1.68)	(-0.66)	(1.78)	(-3.64)	(0.95)	(-3.13)	(-3.37)	(1.03)	(-3.21)
UI	-0.02	-0.12	0.10	-0.45	0.36	-0.81	-0.43	0.48	-0.91
	(-0.09)	(-0.73)	(0.40)	(-2.12)	(1.90)	(-2.76)	(-1.31)	(1.73)	(-2.09)
DEI	-0.08	0.01	-0.09	-0.56	0.47	-1.03	-0.48	0.46	-0.94
	(-0.39)	(0.05)	(-0.35)	(-1.93)	(2.60)	(-2.96)	(-1.37)	(1.77)	(-2.10)
VOL	-0.02	0.08	-0.10	-0.56	0.13	-0.69	-0.54	0.05	-0.59
	(-0.08)	(0.56)	(-0.40)	(-2.15)	(0.71)	(-2.14)	(-1.86)	(0.21)	(-1.56)
MKT	0.27	-0.08	0.35	-0.67	0.20	-0.86	-0.94	0.28	-1.22
	(1.52)	(-0.60)	(1.64)	(-2.95)	(0.85)	(-2.72)	(-2.87)	(0.90)	(-2.82)
LAB	-0.02	0.05	-0.07	-1.10	0.30	-1.40	-1.09	0.25	-1.33
	(-0.09)	(0.30)	(-0.29)	(-3.77)	(1.28)	(-3.63)	(-3.13)	(0.77)	(-2.74)
*Ave*1	0.01	-0.00	0.02	-0.58	0.30	-0.88	-0.60	0.30	-0.90
	(0.11)	(-0.05)	(0.12)	(-3.25)	(1.79)	(-3.56)	(-3.30)	(1.76)	(-3.44)
*Ave*2	0.03	-0.06	0.10	-0.58	0.31	-0.89	-0.62	0.37	-0.98
	(0.28)	(-0.78)	(0.67)	(-3.74)	(1.99)	(-3.91)	(-4.07)	(2.42)	(-4.27)
*Ave*3	0.02	-0.06	0.08	-0.57	0.33	-0.89	-0.58	0.39	-0.97
	(0.15)	(-0.73)	(0.55)	(-3.65)	(2.20)	(-3.99)	(-3.95)	(2.62)	(-4.32)

Table 5
Investor Sentiment and Macro-Factor-Based Portfolios: Predictive Regressions for Excess Returns on Long-Short Strategies

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i;t} = a + bS_{t-1} + \epsilon_t;$$

where $R_{i;t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, and S_t is the level of the BW sentiment index. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.55	-1.98	-1.14	-2.95	-0.59	-2.44
TFP	-0.58	-1.77	-0.81	-2.28	-0.23	-0.97
IPG	-0.70	-2.29	-1.07	-2.90	-0.37	-2.04
$TERM$	-0.48	-1.67	-1.00	-2.75	-0.52	-2.02
DEF	-0.43	-1.56	-1.05	-2.93	-0.62	-2.83
UI	-0.54	-1.62	-0.93	-3.13	-0.39	-1.76
DEI	-0.73	-2.11	-0.91	-3.38	-0.18	-0.77
VOL	-0.36	-1.61	-1.24	-3.16	-0.88	-3.38
MKT	-0.08	-0.39	-1.23	-2.90	-1.15	-3.34
LAB	-0.69	-2.29	-1.30	-3.43	-0.61	-1.86
$Ave1$	-0.49	-2.02	-1.13	-3.09	-0.64	-3.64
$Ave2$	-0.48	-1.96	-1.10	-3.07	-0.62	-3.89
$Ave3$	-0.51	-1.97	-1.07	-3.15	-0.55	-4.26

Table 6

Investor Sentiment and Macro-Factor-Based Portfolios: Predictive Regressions for Benchmark-Adjusted Returns on Long-Short Strategies

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i;t} = a + bS_{t-1} + cMKT_t + dSMB_t + eHML_t + \epsilon_t;$$

where $R_{i;t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the di erence, S_t is the level of the BW sentiment index, and MTK_t, SMB_t, and HML_t are the Fama-French 3 factors. The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.07	-0.43	-0.43	-3.03	-0.36	-1.67
TFP	-0.10	-0.71	-0.16	-1.02	-0.06	-0.28
IPG	-0.11	-0.77	-0.39	-2.58	-0.29	-1.70
$TERM$	0.09	0.76	-0.39	-2.31	-0.48	-2.09
DEF	0.10	0.79	-0.36	-2.32	-0.46	-2.11
UI	0.06	0.53	-0.33	-2.39	-0.39	-1.80
DEI	-0.07	-0.69	-0.38	-2.28	-0.30	-1.53
VOL	0.03	0.25	-0.43	-3.13	-0.46	-2.48
MKT	0.08	0.74	-0.41	-3.33	-0.48	-2.58
LAB	-0.17	-1.27	-0.64	-3.08	-0.47	-1.68
$Ave1$	-0.06	-0.81	-0.41	-3.69	-0.36	-2.92
$Ave2$	-0.02	-0.27	-0.40	-3.72	-0.38	-3.40
$Ave3$	-0.02	-0.26	-0.39	-3.81	-0.38	-3.71

Table 7
Investor Sentiment Changes and Macro-Factor-Based Portfolios

The table reports point estimates of b, along with t-statistics in the regression

$$R_{i;t} \quad = \quad a + b \quad S_t + \quad {}_t;$$

where $R_{i;t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the di erence, S_t is the change of investor-sentiment index of Baker and Wurgler (2006). The results for three average portfolios are also reported. The sample period is from 1965:8 to 2010:12 for all portfolios. Both levels and changes in sentiment are taken directly from Baker and Wurger's online dataset. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

	Low Risk		High Risk		High $-$ Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	2.12	5.94	3.55	8.20	1.44	4.91
TFP	2.26	6.02	3.06	6.69	0.79	2.39
IPG	2.64	5.86	3.74	7.09	1.10	3.50
$TERM$	2.49	7.01	2.98	5.77	0.48	1.41
DEF	2.43	5.75	3.23	8.28	0.80	2.19
UI	2.47	7.30	2.69	6.20	0.22	0.55
DEI	3.03	6.27	2.64	5.93	-0.39	-1.21
VOL	1.76	6.32	3.88	7.17	2.13	5.33
MKT	0.22	0.89	4.05	7.92	3.84	6.27
LAB	2.16	8.03	3.43	6.02	1.27	2.15
$Ave1$	1.86	7.52	3.62	7.49	1.76	5.34
$Ave2$	2.01	7.37	3.49	7.51	1.48	5.23
$Ave3$	2.16	7.45	3.32	7.32	1.17	4.42

Table 8

Sentiment Change as a Factor

Panels A and B of the table report the results for excess returns of portfolios based on their sensitivity to changes in sentiment. Panel A reports the average returns across two sentiment regimes, as classified based on the median level of the BW sentiment index. Panel B reports the results for the regression of portfolio returns on lagged sentiment. Panel C reports the predictive regression results of market excess returns, R_t, on the lagged sentiment variables, S_{t-1}, S^{+}_{t-1}, and S^{-}_{t-1}

Table 9

Table 10

Michigan Sentiment Index and Macro-Factor Based Portfolios: Predictive Regressions for Excess Returns on Long-Short Strategies

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i;t} = a + bS_{t-1} + \sum_{j=1}^{5} m_j X_{j;t-1} + \epsilon_t;$$

where $R_{i;t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, S_t is the level of the Michigan sentiment index in month t, and $X_{1;t}; \ldots; X_{5;t}$ are five additional macro control variables: the default premium, the term premium, the real interest rate, the inflation rate, and the wealth-consumption ratio. The growth in industrial production; the real growth in durable, nondurable, and services consumption; the growth in employment; and a flag for NBER recessions are already controlled when constructing the Michigan sentiment index following the approach of Baker and Wurgler (2006). The results for three average portfolios are also reported. The sample period is from 1978:1 to 2010:12, during which the monthly Michigan sentiment index is available. All t-statistics are based on Newey and West (1987) to control for heteroskedasticity and autocorrelation.

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-0.22	-0.48	-1.04	-2.03	-0.82	-2.58
TFP	-0.34	-0.87	-0.57	-1.06	-0.22	-0.59
IPG	-0.42	-0.93	-0.46	-0.81	-0.04	-0.15
TERM	-0.26	-0.55	-1.09	-2.11	-0.82	-2.29
DEF	-0.38	-0.95	-1.00	-2.17	-0.62	-1.74
UI	-0.41	-1.03	-0.94	-2.01	-0.54	-1.64
DEI	-0.33	-0.73	-0.90	-1.79	-0.58	-1.87
VOL	-0.38	-1.12	-0.94	-1.70	-0.56	-1.69
MKT	-0.05	-0.27	-0.90	-1.43	-0.84	-1.35
LAB	-0.26	-0.70	-1.20	-1.94	-0.94	-2.13
*Ave*1	-0.28	-0.87	-0.85	-1.55	-0.57	-1.98
*Ave*2	-0.29	-0.84	-0.90	-1.73	-0.61	-2.52
*Ave*3	-0.31	-0.87	-0.90	-1.78	-0.60	-2.72

Table 11
Spurious Predictive Regression Critique

First, we simulate arti cial sentiment index by

$$s_{t+1} = \ s_t + \ _{t+1},$$

where $s_0 = 0$, $\ = 0.984$, and $\ \sim N(0,1)$. The simulated sentiment has equal length with the true BW index. Then, we perform both the two-regime sentiment analysis as in Table 3 and the predictive regression analysis as in Table 5 by using the simulated sentiment index. The corresponding t-statistics for the last column of Table 3 and Table 5 are collected. We repeat the above procedure for 1,000 times to obtain 1,000 by 13 t-statistics panel for the last column of Table 3 and Table 5. Panel A reports the 2.5%, 5%, 50%, 95%, and 97.5% quantiles of the t-statistics for the two-regime analysis. To save space, the corresponding results for predictive regression analysis are omitted. Panel B reports the fraction of simulations with all 10 t-statistics for individual macro-related factor simultaneously less than a certain value for both the two-regime analysis and the predictive regression analysis.

Panel A: Distribution of the t-statistics from two-regime simulations

	mean	2.5%	5%	50%	95%	97.5%
CON	-0.019	-2.117	-1.742	-0.020	1.759	2.005
TFP	0.026	-1.929	-1.627	-0.030	1.855	2.166
IPG	0.009	-1.913	-1.568	0.047	1.648	1.850
TERM	-0.053	-2.752	-2.347	-0.089	2.196	2.769
DEF	-0.027	-1.974	-1.756	0.024	1.525	1.888
UI	-0.012	-2.415	-2.001	-0.038	2.190	2.611
DEI	-0.019	-2.203	-1.871	-0.043	1.906	2.291
VOL	0.001	-1.993	-1.700	0.018	1.557	1.809
MKT	0.032	-1.723	-1.404	0.016	1.469	1.654
LAB	-0.009	-2.104	-1.764	0.013	1.719	2.032
Ave1	0.011	-1.696	-1.375	0.036	1.341	1.728
Ave2	-0.006	-1.926	-1.677	0.034	1.551	1.846
Ave3	-0.011	-2.301	-1.894	-0.016	1.789	2.111

Panel B: The fraction of simulations with all 10 t-stats less than a certain value

	0	-0.5	-1	-1.25	-1.5
Two-Regime	0.028	0.002	0.001	0.001	0
Continuous Sentiment	0.034	0.002	0	0	0

Table 12

Investor Sentiment and Macro-Factor-Based Portfolios, Controlling for Macro Variables, Inflation, TED and Aggregate Disagreement: Predictive Regressions

The table reports point estimates of b, along with t-statistics, in the regression

$$R_{i,t} = a + bS_{t-1} + \sum_{j=1}^{4} m_j X_{j,t-1} + cTED_{t-1} + dInf_{t-1} + eDAG_{t-1} + \epsilon_t,$$

where $R_{i,t}$ is the excess return in month t on either the high-risk portfolio, the low-risk portfolio, or the difference, S_t is the level of the BW sentiment index, and $X_{1,t}, \ldots, X_{4,t}$ are four additional macro variables not used by Baker and Wurgler (2006) when removing macro-related variation in sentiment: the default premium, the term premium, the real interest rate and the wealth-consumption ratio. The growth in industrial production; the real growth in durable, nondurable, and services consumption; the growth in employment; and a flag for NBER recessions are already controlled by Baker and Wurgler (2006). We controlled alternative mechanisms by including TED (the 3-month rate difference between LIBOR and treasury bill rate), the inflation rate Inf, and aggregate disagreement DAG (beta-weighted aggregate disagreement). The results for three average portfolios are also reported. The sample period is from 1986:01 to 2010:12 for all portfolios. All t-statistics are robust to heteroskedasticity.

	Low Risk		High Risk		High − Low	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
CON	-2.43	-2.13	-3.30	-2.24	-0.88	-1.04
TFP	-0.75	-0.68	-3.32	-2.43	-2.57	-2.94
IPG	-2.59	-1.99	-3.87	-2.31	-1.28	-1.71
$TERM$	-2.92	-1.96	-2.22	-1.61	0.70	0.74
DEF	-1.60	-1.28	-2.85	-2.36	-1.25	-1.09
UI	-2.18	-1.85	-2.69	-1.99	-0.51	-0.51
DEI	-2.53	-1.71	-2.79	-1.85	-0.25	-0.29
VOL	-0.90	-0.98	-4.41	-2.56	-3.51	-3.19
MKT	-0.05	-0.08	-4.18	-2.28	-4.13	-2.18
LAB	-1.39	-1.27	-4.70	-2.76	-3.31	-2.88
$Ave1$	-1.35	-1.51	-3.97	-2.51	-2.61	-3.03
$Ave2$	-1.58	-1.60	-3.61	-2.46	-2.03	-3.00
$Ave3$	-1.73	-1.68	-3.43	-2.39	-1.70	-2.82