The behaviour of sentiment-induced share returns: Measurement when fundamentals are observable

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Abstract

We test the effect of sentiment on returns using a sample of upstream oil stocks where we have a good proxy for fundamental value. For this sample, the influence of sentiment is highly time-varying, appearing only after the post-2000 increased interest in oil-related assets. Sentiment affects returns on these stocks principally through their fundamentals rather than through deviations from fundamentals. Retail investor sentiment predicts short-term momentum of fundamentals and Baker-Wurgler sentiment predicts mean reversion of fundamental factors. These effects appear in a portfolio that is long hard-to-arbitrage stocks and short easy-to-arbitrage stocks, but only because this portfolio has net exposure to fundamentals.

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In this article we investigate the relationships between investor sentiment and deviations of share prices from fundamental values. To do this we use a sample of shares for which a large part of the fundamental value is observable: upstream oil stocks. We measure their fundamental values using oil and gas prices and the forward oil price contango.

We focus on upstream oil stocks because there is a direct relationship between the present value of these stocks and the oil price. In a world where output prices minus extraction costs obey the Hotelling Principle, the value of natural resource companies depends only on current prices less extraction costs. Miller and Upton (1985a, 1985b) test this proposition and find that it provides a good explanation of the variation in value of a sample of oil producers. Hence a large part of the fundamental value of upstream oil stocks is observable. We make use of this present value condition to split the return on our sample into the part that represents fundamentals and the part that is a deviation from fundamentals.

Following Baker-Wurgler (2006), we test the impact of sentiment using a portfolio that is long high-variance stocks and short low-variance stocks (the "Hi-Lo" portfolio). We find that two types of sentiment predict returns: retail sentiment, which predicts momentum, and the Baker-Wurgler (2006) measure of sentiment, which predicts reversion to fundamentals. We find that the influence of sentiment in each case is time-varying. In particular, the ability of sentiment to predict returns appears only after 2000. Contrary to the theory that sentiment mainly affects the deviations from fundamental value of hard-to-arbitrage stocks, we find that both measures of sentiment influence prices through the fundamentals themselves rather than through deviations from fundamentals.

If the Hi and Lo portfolios had similar loadings on fundamental variables, the net Hi-Lo portfolio would be hedged against fundamental effects and we should not observe fundamentals affecting the returns on this portfolio. However, in our data the loadings on fundamental factors of the Hi and Lo portfolios are different, so the combination of a long and short position in this portfolio does not eliminate its exposure to fundamentals. Methodologically, this raises the issue that tests based on such portfolios do not avoid the need to control for fundamentals.

The results are more consistent with the idea that sentiment predicts market-wide returns rather than deviations of individual stocks from their fundamental value (Arif and Lee (2014)).

The remainder of the article is organized as follows. In Section 1 we give a brief review of related literature. In section 2 we develop our tests and in section 3 we describe our data. Section 4 presents our main tests of the influence of sentiment on returns with and without controls for fundamentals. Section 5 provides some robustness tests. Section 6 concludes.

1. Related literature

Our work is broadly related to a number of studies that have found evidence of serial dependence in returns. Evidence of momentum over periods of six to twelve months is provided by amongst others Lehmann (1990), Jegadeesh (1990), Jegadeesh and Titman (1993, 2001), Asness et al (2013), and Moskowitz et al (2011). Evidence that this medium-term momentum is followed by longer-term mean reversion comes from variance-ratio tests (Poterba and Summers 1988, Lo and MacKinlay 1988, Cutler, Poterba, and Summers 1991) and autocorrelation tests (Fama and French 1988). Evidence that high short-term variance is related to deviations from fundamentals comes from excess variance tests (Shiller 1981, LeRoy and Porter 1981).

Sentiment-based explanations of momentum, mean-reversion, and deviations from fundamentals envisage these effects as arising from behavioural biases by naïve investors combined with costs of arbitrage. For example, Daniel, Hirshleifer, and Subrahmanyam (1998) present a model in which a combination of overconfidence and biased self-attribution create both under- and over-reaction. Similarly, Barberis, Shleifer, and Vishny (1998) appeal to the behavioural biases of representativeness and conservatism to show how these can result in under- and over-reaction. In both papers asset prices can be decomposed into one part that reflects fundamentals and another consisting of deviations from fundamentals. The effect of sentiment on asset prices operates through the deviations from fundamentals.

Empirical evidence on the link between sentiment and returns requires a measure of sentiment. A number of suggestions have been proposed. Many of these reflect the view that sentiment changes are driven by retail investors. Possible proxies include flows into mutual funds (Brown et al 2003), buy/sell imbalances by retail investors (Kumar and Lee 2006), IPO volume and initial returns (Baker and Wurgler 2006), market turnover (Baker and Wurgler 2006), closed-end fund discounts, (Lee, Shleifer, Thaler 1991, Chen et al 1993, Swaminathan 1996, and Neal and Wheatley 1998), the growth stock premium (Baker and Wurgler 2006), and survey data (Qiu and Welch 2004, Brown and Cliff 2004, 2005). These data have been used either singly or in combination as sentiment measures to test hypotheses about the relationship between sentiment and subsequent stock returns.

Our tests of the effect of sentiment are most closely related to Baker and Wurgler (2006, 2007, 2012) and Baker, Wurgler, and Yuan (2012). Baker and Wurgler divide their sample of stocks into ten portfolios on the basis of their prior volatility, which serves as a proxy for difficulty of arbitrage. They find that returns on the more volatile stocks are lower following a time of optimism, and that returns are higher following a time of pessimism. For the less volatile stocks that are easier to arbitrage the reverse is true. They develop a measure of investor sentiment which they find predicts returns for portfolios that are long the more volatile stocks and short less volatile stocks. This finding is consistent with a combination of behavioural biases and limits to arbitrage.

Barberis, Shleifer and Wurgler (2005) stress the importance of controlling for fundamentals when measuring the effect of sentiment on security prices. For example, Derrien and Kecskés (2009) show that the effect of sentiment on equity issuance disappears once controls for fundamentals are included. Baker and Wurgler's use of a Hi-Lo portfolio will be effective in controlling for fundamentals only if the long and short positions have equal loadings on fundamental factors. The alternative is to attempt to control directly for fundamentals. Brown and Cliff (2005) use as their dependent variable estimates of deviations from fundamental value based on the dividend discount model. They find that these deviations are positively related to a sentiment measure derived from survey data. However, the dividend discount model gives a very noisy observation of fundamental value. For our sample of stocks, we

have a more direct measure of fundamental value than Brown and Cliff and so are able to perform a more powerful test of the way that sentiment is transmitted to share prices and returns.

2. Hypotheses and tests

We test the implications of the hard-to-arbitrage hypothesis using a simple empirical procedure that relates sentiment measures to deviations of share prices from fundamentals and also to the fundamentals themselves. We split the log share price, P_t, into a component reflecting fundamental value, F_t, and a separate component, NF_t, which is the deviation from fundamental value:

$$NF_t = P_t - F_t \tag{1}$$

We assume that prices are affected by the actions of two types of traders. One type is an arbitrageur, whose behaviour is captured by the Baker-Wurgler sentiment measure S_t. The other type is a naïve trend-follower, whose behaviour is captured by a bullish retail sentiment measure, B_t. Fundamentals and non-fundamentals may respond to both sentiment variables:

$$F_t - F_{t-1} = \Delta F_t = \theta_{B,F} B_{t-1} + \theta_{S,F} S_{t-1} + e_{Ft} \tag{2}$$

$$NF_t - NF_{t-1} = \Delta NF_t = \theta_{B,NF} B_{t-1} + \theta_{S,NF} S_{t-1} + e_{NFt} \tag{3}$$

We model the response to Baker-Wurgler sentiment by assuming that arbitrageurs push prices down when this sentiment variable is high, making $\theta_{S,F} < 0$ and $\theta_{S,NF} < 0$. The effect of naïve trend-followers pushes prices up when Bullish sentiment is high, making $\theta_{B,F} > 0$ and $\theta_{B,NF} > 0$.

The Baker-Wurgler sentiment variable is a measure of mispricing and so should rise when the deviation from fundamentals increases:

$$S_t = \theta_{S,S} S_{t-1} + \theta_{S,NF} \Delta NF_t + e_{St} \tag{4}$$

where $\theta_{S,NF} > 0$. We expect S_t to be highly persistent, reflecting the long cycle of swings in mispricing. We hypothesize that the bullish sentiment indicator reflects trend-following behavior:

$$B_t = \theta_{B,B}B_{t-1} + \theta_{B,P}(P_t - P_{t-1}) + e_{Bt} \qquad\qquad (5)$$

$\theta_{B,P} > 0$. We expect B_t to be less persistent than S_t, reflecting shorter cycles in momentum sentiment.

We stack Equations (2)-(5) to form the system shown in Table 1, which we estimate using VAR. Our null hypothesis is that the sentiment variables affect deviations from fundamentals but not the fundamentals themselves. This would be consistent with the limits-to-arbitrage hypothesis, whereby sentiment causes deviations from fundamentals when such deviations are hard to arbitrage. The indicated signs of the key parameters under the null hypothesis are shown in Table 1. In particular, the standard hypothesis is that sentiment affects deviations from fundamentals, implying $\theta_{S,F}=0$, $\theta_{B,F}=0$, $\theta_{S,NF}<0$, $\theta_{B,NF}>0$. As an alternative, we test the hypothesis that the influence of sentiment occurs via its effect on fundamentals, which implies that $\theta_{S,F}<0$, $\theta_{B,F}>0$, $\theta_{S,NF}=0$, $\theta_{B,NF}=0$.

TABLE 1 HERE

3. Data

Our sample consists of the stocks of the 121 U.S. oil exploration and production companies quoted on the NYSE during the period March 1983 to January 2011. We define an exploration or production company as one with a North American Industrial Classification (NAIC) of 211111 or a Standard Industrial Classification (SIC) of 1311. We assume that fundamental value is a function of the month-end spot price of West Texas Intermediate oil and the spot wellhead price of West Texas natural gas. We also use the change in the contango in oil prices, where contango is measured as the

log of the price of the sixth most distant futures contract less that of the price of the closest futures contract.[1] The Appendix gives our data sources.

To investigate the behaviour of returns we form portfolios of oil stocks. We proxy the behaviour of all upstream oil stocks by the equally weighted portfolio of all stocks with return data for a given month (the "All-stocks" portfolio). The hard-to-arbitrage hypothesis suggests that sentiment-induced deviations from fundamental value should be greater in the more volatile stocks. We therefore form sub-portfolios of our sample of stocks consisting of the tercile of stocks with the highest variance of returns over the preceding 60 months and the tercile with the lowest variance. Following Baker-Wurgler, we form a portfolio that is long the tercile of high-variance stocks and short the tercile of low-variance stocks (the "Hi-Lo" portfolio). These portfolios are formed out of sample, and so represent a viable trading strategy.

We employ two measures of sentiment: the Baker-Wurgler index ("BW sentiment") and the proportion of individual investors who report that they are bullish in the regular survey conducted by the American Association of Individual Investors ("Bullish sentiment"). Both measures are available for the period July 1987 to January 2011. To facilitate comparison between the two sentiment measures, we recalibrate the index values in terms of the number of standard deviations from the mean for the total period. Figure 1 provides a plot of these two rescaled measures. The Baker-Wurgler index is characterised by long swings in sentiment with a marked peak in value in February 2001. By contrast, Bullish sentiment is more noisy and less persistent. The first-order autocorrelation coefficient in the Baker-Wurgler index is .96, and the serial correlation in the index persists at least through lag 6. By contrast, the first-order autocorrelation coefficient in the AAII measure is .45 and the lower order serial correlations fall away rapidly.

FIGURE 1 HERE

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[1] Our results are robust to varying the definition of these variables. For example, using spot Brent prices or a closer futures contract does not affect our conclusions. Equally, we obtain qualitatively

The monthly levels of the two sentiment indexes are only weakly related with a correlation of .09. The Baker-Wurgler index more closely resembles a cumulative sum of past values of the Bullish measure,[2] which is consistent with the Baker-Wurgler index capturing cumulative deviation from fundamentals rather than short-term swings in sentiment.

Table 2 shows descriptive statistics for our variables. Panel A shows the means and standard deviations of the oil portfolio returns and of the changes in the fundamental values. Although the portfolios are formed out-of-sample, the standard deviation of the high-volatility portfolio is 50% higher than that of the low-volatility portfolio. The volatility of the Hi-Lo portfolio which should, in principle, be hedged against changes in fundamentals is almost as high as that of the Hi volatility portfolio, suggesting that the long-short strategy may have only limited effect in controlling risk.

TABLE 2 HERE

Panel B of Table 2 shows the correlation matrix for the entire period. Two features of the matrix are of interest and point to issues that are explored in more depth later.

1. The correlations between the returns on oil stocks and the three fundamental variables are quite high. Taken together, the three fundamental variables explain 41% of the variance in the returns on the portfolio of all oil stocks.

2. The long-short portfolio of oil stocks (Hi-Lo) is not well hedged against fundamentals, and its returns remain quite highly correlated with all three fundamental variables. In other words, the high-volatility stocks are not only more difficult to arbitrage, but they also have different loadings on the fundamental factors.

Panel C of Table 2 shows the correlations between lagged sentiment and portfolio returns, and lagged sentiment and fundamentals. For our entire data period lagged Baker-Wurgler sentiment negatively predicts returns across all portfolios and the gas and oil fundamentals. Lagged Bullish sentiment positively predicts returns across all

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similar, but somewhat less strong, results using the Datastream index of U.S. oil stocks rather than our equally weighted portfolio of upstream stocks only.

portfolios and the oil and gas fundamentals. Consistent with the cost of arbitrage hypothesis, the correlation with Baker-Wurgler sentiment is higher for the high variance portfolio than for the low variance portfolio. However, the correlation with fundamental variables is even higher. For the Bullish sentiment correlations, the high and low variance portfolios have equal correlations with sentiment, but the Hi-Lo portfolio has an even higher correlation.

Thus overall the data are consistent with sentiment predicting returns in the hypothesized ways. However, they do not suggest that the mechanism is necessarily via deviations from fundamentals rather than through the fundamentals themselves.

4. Sentiment and returns

In this section we examine the influence of sentiment on returns. In Section 4.1 we provide evidence that the returns on the portfolios of oil stocks are characterised by momentum and longer-term mean reversion. We then examine the returns to see whether these patterns in returns are a function of our two measures of sentiment. In Sections 4.2 and 4.3 we go on to decompose the returns into a fundamental and residual component and we analyse the relationship between these two components and our sentiment measures. In Section 4.4 we then examine the relationship between stock returns and "deep" fundamentals based on demand and supply in the oil market.

4.1 The influence of sentiment on the Hi-Lo portfolio

Before testing for the effect of sentiment on returns, we first examine the serial properties of returns on the All-stock portfolio and the relationship of these returns to fundamentals. Table 3 shows for our portfolio of oil stocks the variance rates at differing intervals expressed as a proportion of the 1-month variance rate using the variance ratio test with overlapping data proposed by Lo and Mackinlay (1988). Consistent with standard results, the variance ratio rises for 6-9 months reflecting medium-term momentum and then falls back over the following year reflecting longer-term mean reversion.

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[2] A regression of the Baker-Wurgler index on the concurrent and 9 lagged values of the AAII measure gives a positive loading on each of the independent variables with a multiple correlation of .34.

TABLE 3 HERE

We examine the influence of sentiment by regressing total returns on the two lagged sentiment measures:

$$R_t = a + \theta_{S,R}S_{t-1 +} + \theta_{B,R}B_{t-1} + e_{i,t} \tag{6}$$

To investigate the role of fundamentals we augment this regression with controls for the fundamental variables:

$$R_t = a + \theta_{S,R}S_{t-1 +} + \theta_{B,R}B_{t-1} + \theta_{F,R}\Delta Ft + e_{i,t} \tag{7}$$

where ΔFt is the vector of fundamental variables.[3]

Table 4 reports the result of regressions (6) and (7) for the All-stock portfolio and the Hi-Lo portfolio over the period 1988-2011.[4] For the All-stock portfolio before controlling for fundamentals the coefficient on the BW sentiment measure has the predicted negative sign but is insignificant, whilst the coefficient for the Bullish measure is positive and significant, as predicted. Including the fundamentals raises the R^2 of the regression from .00 to .41. All three fundamental variables are highly significant with an unexpected 1% increase in the oil price resulting in an increase of .59% in the value of oil stocks. The coefficient on the change in the contango is positive suggesting that when the value of the future relative to the spot rises, there is a positive impact on the price of oil stocks. In other words, given the spot price of oil, the value of companies owning oil reserves increases when the futures price rises relative to the spot. Once these controls for fundamentals are included, the significance of the Bullish measure disappears and both sentiment measures become insignificant. The high R^2 on the regression with fundamentals and the change in the

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[3] We also estimated equation (7) using estimates of the innovations in the fundamental variables. These were estimated from an AR process with the optimal (i.e. not pre-specified) number of lags. The results were not sensitive to whether the fundamental variables were whitened.

[4] Note that the regressions employ data only from 1988. The first 60 months of data are used to form the initial high- and low-variance portfolios.

significance of the sentiment measures shows the importance of controlling for fundamentals in testing the effect of sentiment.

TABLE 4 HERE

The hard-to-arbitrage hypothesis predicts that the influence of sentiment will be most marked for high-variance stocks. Therefore, following Baker-Wurgler, we also report in Table 4 the result of regressions (6) and (7) for the portfolio that is long high-variance stocks and short low-variance stocks. The high-variance stocks are characterised by a heavier loading on the three fundamental factors. This may stem from the higher relative importance of exploration (as opposed to production) activity as proxied by a low ratio of revenues to assets.[5] Thus, despite its apparent hedged position, the Hi-Lo portfolio remains significantly exposed to oil and gas returns After controlling for fundamentals, the coefficients on both sentiment measures have the predicted sign, but only the Bullish variable is significant at the 10% level.

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4.2 Tests using fundamentals and deviations from fundamentals

We now test the hypothesis that sentiment operates by affecting deviations from fundamental value. To do so, we first decompose returns on the Hi-Lo portfolio into a fundamental component and a residual, and we then estimate the relationship between our sentiment measures and each of these two components. Since the loadings of this portfolio on the fundamental factors may be time-varying we estimate the loadings using rolling 60-month regressions of portfolio returns on the fundamental variables:

$$R_{it} = a_i + b_i \, \Delta \, WTI_t + c_i \, \Delta \, Gas_t + d_i \, \Delta \, Cont_t + u_{it} \qquad (8)$$

We use the coefficients from this regression over the prior 60 months combined with the change in the month's fundamentals to estimate that part of the month's return that

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[5] It is also possible that the lower exposure of low-variance stocks to energy prices reflects hedging activity, although Haushalter (2000) suggests that hedging is more commonly used by the more risky oil and gas firms.

was due to fundamentals. The difference between the actual return in a month and the fundamental return is the residual, or non-fundamental, return.

We estimate the VAR system (2)-(5) using GMM with the Newey-West correction for standard errors. Table 5 shows the results for the entire period 1988-2011.[6] Contrary to the "deviations from fundamentals" hypothesis all the coefficients of the regression of deviations on lagged variables in column (2) are insignificant, and the Rbar^2 is negative. In contrast, the regression of fundamental returns on lagged sentiment (column (1)) has an Rbar^2 of 5%. There is a negative coefficient on lagged B-W sentiment and a positive coefficient on the lagged bullish variable. Both coefficients are strongly significant. This result is consistent with sentiment-based trading operating largely through the fundamentals themselves, rather than through the deviations in the share price from fundamentals. The negative coefficient on lagged B-W sentiment is consistent with high sentiment signalling that the oil market is above its equilibrium and likely to fall. The positive coefficient on the Bullish variable is consistent with short-term momentum pushing the oil market upwards when retail investors are bullish.

TABLE 5 HERE

Column (3) shows that the Baker-Wurgler sentiment variable is persistent, with a partial serial correlation of 0.97 consistent with a half-life of 20 months. The variable also responds to lagged changes in fundamentals, but not to lagged changes in deviations from fundamentals. Again, this is consistent with sentiment operating through the fundamentals themselves and not through deviations of share prices from fundamentals. Column (4) shows that the Bullish variable is much less persistent, with a half-life of less than a month. It has positive serial correlation and positively responds to past fundamental returns.

We also estimate the system for two sub-periods divided at 2000. The motivation for looking separately at the sub-periods is the sharp increase in institutional investment in oil futures after 2000 (Buyuksahin and Robe (2012) and Singleton (2011)). In the

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[6] The period is reduced by 5 years because the first 60 months are used to estimate equation 8.

ten years to 2010 open interest in crude oil futures by non-commercial traders was 5.6 times its level over the previous 15 years (Figure 2A). Figure 2B shows that there was also a sharp rise in the cumulative cash flows into managed futures funds, which increased from $9.3 billion in September 2002 to $137.0 billion in March 2008 before losing most of these gains in 2009.

FIGURE 2A and B HERE

Table 6 decomposes the Hi-Lo portfolio data into two sub-periods, divided at the end of 2000. Column (1) shows the results for the entire period, and columns (2) and (3) for the two sub-periods. The two sentiment variables have no significant effect on deviations from fundamentals in any period, though the coefficients on the Bullish variable consistently have the correct sign. The coefficients from the regression of the fundamental component of returns on the two lagged sentiment variables have the correct sign but are insignificant in the first sub-period. By contrast, in the second period the corresponding coefficients are strongly significant. Although the time-series behavior of the sentiment variables appears to be the similar in the two sub-periods, the effect of sentiment on stock returns changes completely in the second period. Consistent with the result that sentiment affects prices largely via fundamentals, the effect occurs only once there is significant investment interest in the fundamental markets post-2000.[7]

TABLE 6 HERE

4.3 The effect of the differencing interval

Table 7 shows the effect of increasing the differencing interval to 3 months and 12 months. The results are shown for the entire period (Panel A) and the two sub-periods (Panels B and C). The VAR is estimated using GMM with overlapping observations

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[7] The sharp changes in cumulative flows into commodity hedge funds prompted us to examine (more in hope than expectation) the effect within the VAR of interacting the cumulative flows with the sentiment variables. There was no evidence that the impact of sentiment on returns was related to the cumulative flows into managed futures funds.

and Newey-West corrected standard errors. In the regression of fundamental returns the effect of moving from a 1-month to 3-month differencing interval is to increase the magnitude and significance on both of the lagged sentiment measures in all three periods. The Rbar^2 of the regression of fundamentals on sentiment increases dramatically, rising to .29 for a 12-month differencing interval in the second sub-period. Thus the sentiment measures appear to have a prolonged effect on the fundamental returns. In contrast, the longer differencing intervals have almost no effect on the coefficients for the deviations from fundamentals, which remain insignificant at all intervals and in all periods.

TABLE 7 HERE

4.4 "Deep Fundamentals"

Our measure of the fundamental return on the portfolio of oil stocks is equivalent to a weighted average of the contemporaneous change in the price of oil and gas and the change in the contango. The evidence that this weighted average is a function of the prior level of sentiment implies that oil and gas prices are themselves influenced by sentiment (Pindyck (1993)). Thus it appears that sentiment drives oil prices away from equilibrium values in a way that leads to predictable returns on oil stocks. This effect increases after 2000 when interest in commodities as an asset class increased significantly. One-month returns are slightly predictable using sentiment, but returns over a 1-year horizon are highly predictable. Overall, the results appear to reflect a slowly changing but predictable component of oil and gas prices that is related to sentiment and generates a predictable return on oil stocks. Sentiment appears to have no effect on the price of oil stocks other than through the prices of the commodities themselves.

We can gain some further insight by examining the relationship between the change in oil prices and prior sentiment while controlling for the deeper fundamentals that determine oil prices.

$$\Delta WTI_t = a + \theta_S S_{t-1} + \theta_B B_{t-1} + \theta_F \Delta DF_t + e_t \qquad (9)$$

where ΔDF_t is the vector of the underlying determinants of the change in oil prices.

The main problem in estimating (9) is the lack of good proxies for deeper fundamentals that are available at sufficiently high frequency. We proxy the fundamental determinants oil prices by changes in world oil production and consumption, changes in world proven reserves (annual data only), changes in oil inventories (monthly data only), and a measure of economic growth. We estimate (9) using annual data, overlapping 12-month data and overlapping 3-month data. In the case of the annual data estimates are for the period 1988 to 2011 and in the case of the regressions using monthly data estimates are for the period 1994 to 2011. The results are summarized in Table 8 Panel A. For comparison, Panel B shows the same regressions with only the sentiment variables included.

TABLE 8 HERE

With relatively few independent observations, the tests lack power, but they give an indication that the sentiment variables predict not only the change in oil prices but also the change in deep fundamentals. In particular, if the deep fundamentals are excluded the Baker-Wurgler sentiment predicts the oil price, but when the deep fundamentals are included it does not. Thus the table provides mild support that sentiment predicts not only energy prices but also the fundamental variables that drive oil prices. Through these it predicts the return on oil stocks.

5. Robustness tests

We have already noted that our findings are robust to (a) pre-whitening the fundamental variables, (b) using different definitions of the crude oil price and the oil contango, (c) using the Datastream index of oil stocks.

5.1 Long-only portfolios

To the extent that the Hi-Lo portfolio is better hedged against fundamental factors than long-only portfolios, the fundamental component of returns will be relatively

small. We therefore repeated the VAR estimates with long-only portfolios. The results for the tercile of stocks with the highest variance were very similar to those for the Hi-Lo portfolio. In particular, the effects of sentiment on returns were significant only for the second period, and sentiment impacted returns largely through the fundamental component.

5.2 Nasadaq stocks

To test further the robustness of these results to a different sample of oil stocks, we extended the sample to include 274 stocks of U.S. oil and exploration companies that were traded on Nasdaq. Although this produced a larger sample, the quality of the Nasdaq data appears to be inferior with shorter time series for many stocks, leptokurtic returns and more zero returns. Unsurprisingly, the high variance portfolio tended to have a high concentration in Nasdaq stocks.

The expanded portfolio is better hedged against fundamental factors and the addition of these factors has therefore less effect on estimates of the sentiment effect. Otherwise, the results are similar to those reported in Tables 4 and 5. The coefficients on B-W are consistently negative and those on Bullish consistently positive. However, there continues to be a big difference between the two periods with the coefficients being significant only in the later period.

5.3 The effect of lagged market returns

To evaluate the role of market returns in generating sentiment, we augmented the VAR system by including the lagged market return in each of the regressions. This did not significantly change the relationships between either of the sentiment variables and either of the returns. It did not increase the R^2's for the prediction of returns. The Bullish sentiment variable is not significantly related to the lagged market return in the second sub-period, where the main sentiment effect is apparent. This suggests that the momentum generated by the positive relationship between fundamental returns and lagged Bullish sentiment is not simply a proxy for the effect of lagged market returns.

5.4 Lagged fundamentals

We also added to the VAR system more lags of the fundamental returns. These were generally insignificant and did not change the basic results. The sentiment variables remained significant in the second sub-period and the effect of sentiment showed up only in the fundamental regression and not the deviations from fundamentals.

6. Conclusions

Using a sample of upstream oil stocks where we have a good proxy for fundamental value, we show that sentiment predicts returns. However, the effect is highly time-varying, appearing only after the post-2000 increased interest in oil-related assets.

Sentiment effects come it two forms: retail investor sentiment predicts short-term momentum, and Baker-Wurgler sentiment predicts medium-term mean reversion of fundamental factors. Whilst the sentiment variables explain only a negligible proportion of the variance of returns, the additional return due to a change in sentiment is not unimportant. For example, in the second period for the portfolio of all oil stocks a one standard deviation rise in the level of investor sentiment added about .3 % to the following month's return; during the same period a similar one-standard-deviation rise in the Baker-Wurgler index *reduced* return by about .3%.

Contrary to the hard-to-arbitrage hypothesis, sentiment affects returns on these stocks through fundamentals rather than through deviations from fundamentals. Overall, it appears that retail sentiment drives the prices of oil and gas futures away from their deeper fundamental values until the deviation is sufficiently large that arbitrageurs drive the prices back towards their equilibrium values. This process for the fundamentals is then reflected in the prices of upstream oil stocks.

These effects appear even in a portfolio that is long hard-to-arbitrage stocks and short easy-to-arbitrage stocks, because this portfolio has a net exposure to fundamentals. This has implications for tests of the hard-to-arbitrage hypothesis, showing that it is important to have effective controls for fundamentals even when the long-short portfolio is used.

Our finding that sentiment affects upstream oil stocks through the fundamentals raises the issue as to whether this is also the case with other industries that invest in assets that are traded in speculative markets. Obvious examples would be stocks in other extractive industries but a similar effect could characterize financial institutions. It also prompts the question whether the magnitude of any sentiment effects depends on the extent to which the fundamentals are tradeable. If this is the case, sentiment effects might vary not just with ease of arbitrage but with the nature of the company's fundamentals. The sharp increase in the significance of sentiment effects in the post-2000 period was accompanied by an increase in speculative activity in energy futures. If these effects are truly linked, then it raises the question as to the effect of trading activity on the influence of sentiment. These would appear to be fruitful, if difficult, areas for future research.

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APPENDIX: PRINCIPAL DATA SOURCES

Stock samples All common stocks with NAIC code of 211111 or SIC code of 1311 (oil production or exploration) that were listed on the NYSE or Nasdaq and whose issuers were incorporated in the USA. Returns data were taken from the CRSP monthly database.   Portfolio returns were constructed from equally weighted holdings in all stocks with valid returns data for that month. Portfolio returns were then converted to continuously compounded returns.

Oil prices Month-end spot prices for West Texas Intermediate taken from the Energy Administration website at www.eia.gov.

Natural gas prices Monthly spot prices for Natural Gas Wellhead Price taken from Globalfindata. Prices are month averages from March 1983-December 1995 and end-of-month from January 1996- January 2011.

Contango NYMEX futures prices are taken from Quandl at www.quandl.com.. The contango is defined as the price of the contract that is sixth nearest to delivery divided by the price of the contract that is closest to delivery. The change in contango is defined as $\ln(\text{contango}_t) - \ln(\text{contango}_{t-1})$.

Baker-Wurgler Sentiment Index SENT[1] constructed from IPO volume, IPO first-day returns, market turnover, and the market-book ratio of high-volatility stocks relative to that of low-volatility stocks. See http://people.stern.nyu.edu/jwurgler/. The index is rescaled to have mean zero and unit standard deviation.

American Association of Individual Investors (AAII) Investor Sentiment Survey Proportion of investors reporting they are bullish divided by the total proportion reporting that they are either bullish or bearish (i.e. not neutral). Taken from final week's survey in each month as reported on www.aaii..com/sentimentsurvey. The index is rescaled to have mean zero and unit standard deviation. Data are available from July 1987.

Figure 1: Measures of sentiment

This figure shows plots of the Baker-Wurgler and Bullish sentiment indexes from July 1987 to January 2011. In both cases the index has been standardized to have a mean of zero and standard deviation of unity.

Baker Wurgler sentiment index

AAII sentiment survey
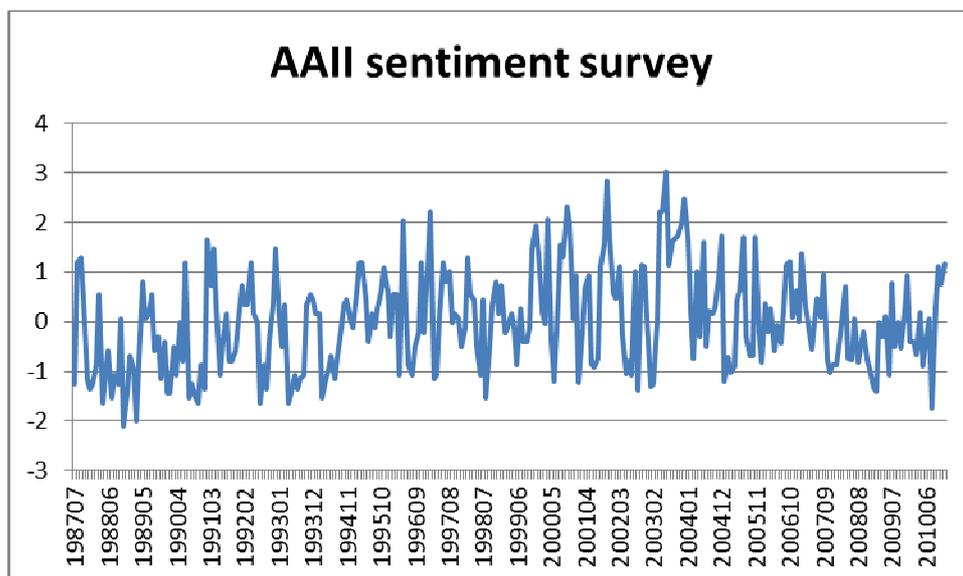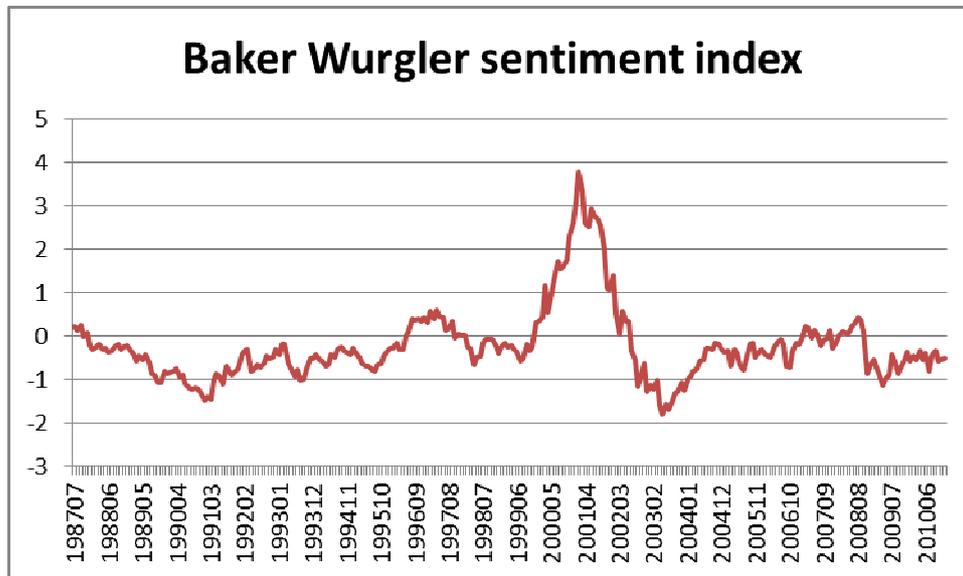
Figure 2A: Open interest in oil futures

This figure shows on a log scale the level of open interest in crude oil futures by non-commercial traders from January 1986 to December 2012.
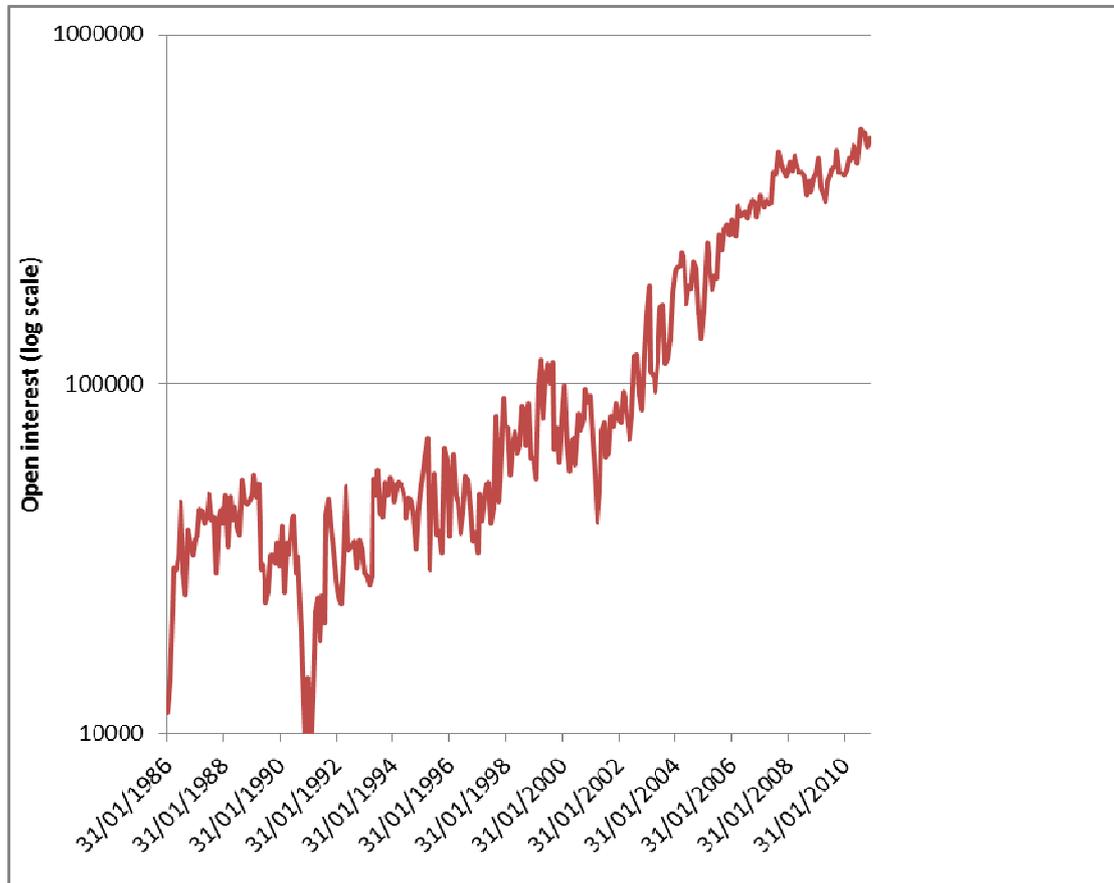
Source: CFTC

Figure 2B: Cumulative flows into commodity hedge funds

This figure shows on a log scale the cumulative quarterly cash flows into Managed

Futures Funds in millions of dollars from first quarter 1994 to the third quarter 2010.
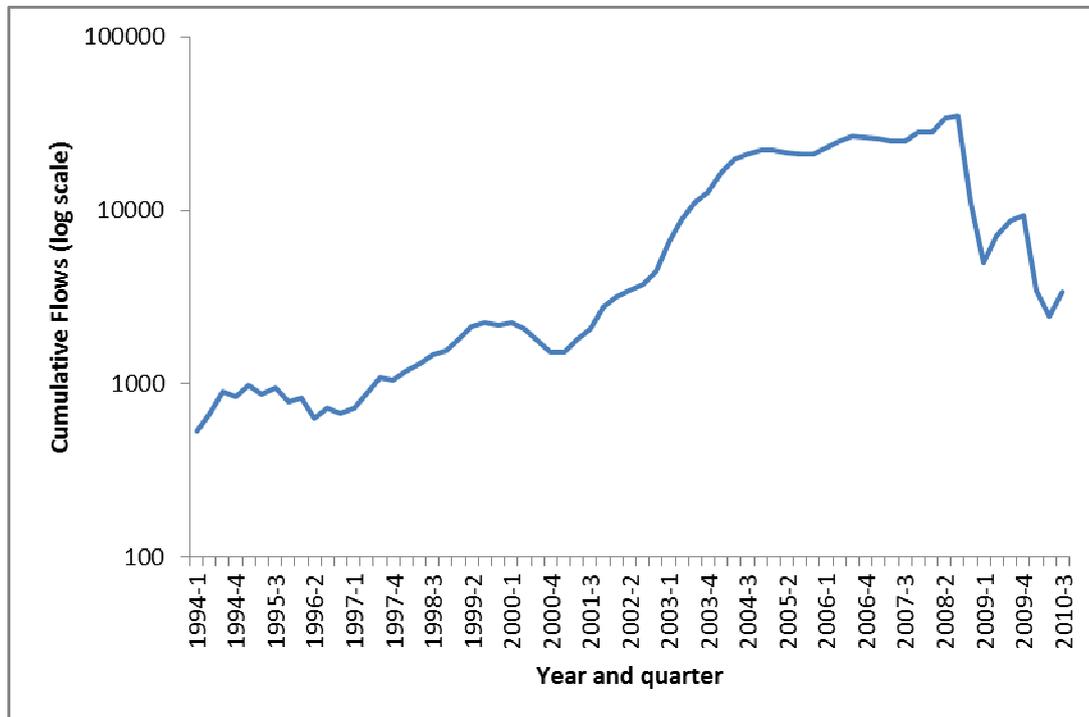
Source: TASS Research

Table 1: Structure of the VAR and hypotheses about coefficients

	Equation			
	(1)	(2)	(3)	(4)
Independent variables	Dependent variable			
	$F_t - F_{t-1}$	$NF_t - NF_{t-1}$	S_t	B_t
$F_{t-1} - F_{t-2}$	$\theta_{F,F}=0$	$\theta_{F,NF}=0$	$\theta_{F,S}=0$	$\theta_{F,B}>0$
$NF_{t-1} - NF_{t-2}$	$\theta_{NF,F}=0$	$\theta_{NF,NF}=?$	$\theta_S >0$	$\theta_{NF,B}>0$
S_{t-1}	$\theta_{S,F}=0$	$\theta_{S,NF}<0$	$\theta_{S,S}>>0$	$\theta_{S,B}=?$
B_{t-1}	$\theta_{B,F}=0$	$\theta_{B,NF}>0$	$\theta_{B,S}=?$	$\theta_{B,B}>0$

Table 2: Summary statistics

The table shows summary statistics for portfolio returns and log changes in the fundamental variables, monthly data 1988.01-2011.01. The underlying stock prices are for a balanced sample of 121 upstream oil firms. Lo is the return on the portfolio of stocks in the lowest volatility tercile. Hi is the return on the portfolio in the highest volatility tercile. All is the return on the portfolio of the entire sample. Hi-Lo is the return on the portfolio that is long the Hi portfolio and short the Lo portfolio. Δ WTI is the first difference of the log spot price of WTI. Δ Gas is the first difference of the log spot natural gas price. ΔCont is the first difference in the log of the WTI contango, where contango is defined as the ratio of the price of the sixth most distant futures contract to that of the nearest contract.

Panel A: Means and standard deviations of portfolio returns and changes in fundamental variables.

	Lo	Hi	All	Hi-Lo	ΔWTI	ΔGas	ΔCont
Mean	.010	.014	.012	.006	.005	0.003	.0003
Std. Dev.	.069	.104	.082	.064	.093	0.196	0.036

Panel B: Correlation coefficients. Below the diagonal is the Pearson coefficient and above the diagonal in italics is the Spearman's rank coefficient. Bold face indicates coefficient is significantly different from zero at the 90% confidence level.

	Lo_t	Hi_t	All_t	Hi_t-Lo_t	ΔWTI_t	ΔGas_t	$\Delta Cont_t$
Lo_t		*.77*	*.92*	*.25*	*.45*	*.42*	*-.19*
Hi_t	**.82**		*.94*	*.77*	*.47*	*.39*	*-.23*
All_t	**.95**	**.95**		*.54*	*.48*	*.43*	*-.23*
Hi_t-Lo_t	**.30**	**.79**	**.57**		*.25*	*.20*	*-.15*
ΔWTI_t	**.48**	**.49**	**.50**	**.30**		*.27*	*-.71*
ΔGas_t	**.41**	**.41**	**.44**	**.24**	**.24**		*-.18*
$\Delta Cont_t$	**-.15**	**-.21**	**-.18**	**-.21**	**-.73**	-.12	

Panel C: Correlation coefficients. Correlations with lagged sentiment indices. Entries show the correlations between the return in a month and the level of the two sentiment indices at the beginning of that month. S_{t-1} is the Baker Wurgler sentiment index lagged 1 month, and B_{t-1} is the percentage of bullish respondents to AAII survey lagged 1 month.

	S_{t-1}		B_{t-1}	
	Correln	t-stat	Correln	t-stat
ΔWTI_t	-0.08	-1.39	0.11	1.78
ΔGas_t	-0.07	-1.10	0.11	1.88
All_t	-0.03	-0.51	0.13	2.08
Hi_t	-0.05	-0.82	0.16	2.69
Lo_t	0.00	-0.01	0.16	2.69
Hi_t-Lo_t	-0.08	-1.25	0.17	2.90

Table 3: Variance ratios of the All-stocks portfolio
The table shows the variance of the All-stocks portfolio over different intervals as a proportion of the 1-month variance rate, measured over 1983.01-2012.12. The portfolio invests equal amounts each month in all U.S. oil production and exploration stocks listed on the New York Stock Exchange.

	Interval (months)								
	1	3	6	9	12	15	18	21	24
1983-2012	1.0	1.14	1.23	1.20	1.12	1.09	1.05	.99	.95

Table 4: Regression of portfolio returns on lagged sentiment with and without controls for fundamentals

The table summarizes the results of a regression of returns on each of two oil portfolios against two lagged sentiment measures, S_{t-1} and B_{t-1}, for the period 1988.01-2011.01. The coefficients on the sentiment measures are shown without and with controls for the effect of fundamentals. The All-stocks portfolio invests equal amounts each month in all U.S. oil production and exploration stocks listed on the New York Stock Exchange. The Hi-Lo portfolio has long positions in the tercile of stocks with the highest variance over the prior 60-month period and short positions in the tercile of stocks with the lowest variance over the prior 60-month period. The regressions are estimated from monthly data using OLS with a constant (not reported). t-statistics in parentheses. * denotes 10% significance, ** 5% significance, and *** 1% significance.

	All-stocks portfolio		Hi-Lo portfolio	
	No controls	Fundamental controls	No controls	Fundamental controls
Baker-Wurgler sentiment	-.003 (-.69)	.002 (.51)	-.006 (-1.47)	-.003 (-.91)
Bullish sentiment	.010 (2.11)**	.003 (.70)	.010 (2.68)***	.007 (1.91)*
Oil return		.587 (9.81)***		.170 (2.97)***
Gas return		.129 (6.54)***		.053 (2.82)***
Oil contango change		.805 (5.35)***		.018(.13)
Rbar^2	.01	.41	.02	.12

Table 5: VAR of fundamental values for the Hi-Lo portfolio, deviations from fundamentals, Baker-Wurgler sentiment, and Bullish sentiment

The table shows a VAR of the return to fundamentals ($F_t - F_{t-1}$) for the Hi-Lo portfolio, return to deviations from fundamentals ($NF_t - NF_{t-1}$) for the Hi-Lo portfolio, Baker-Wurgler sentiment (S_{t-1}), and Bullish sentiment (B_{t-1}). Monthly data 1988.01 to 2011.01. The Hi-Lo portfolio has long positions in the tercile of stocks with the highest variance over the prior 60-month period and short positions in the tercile of stocks with the lowest variance over the prior 60-month period. Returns on the portfolio each month are split between fundamental returns and deviations from fundamentals. Fundamental returns are based on a regression of the portfolio return on the oil price return, gas price return, and the change in contango in the oil market, using a rolling window of 60 months prior to the month for which the stock return is split. The system is estimated using GMM with Newey-West correction for the standard errors.   t-statistics in parentheses. * denotes 10% significance, ** 5% significance, and *** 1% significance.

	(1)	(2)	(3)	(4)
	Dependent variable			
	$F_t - F_{t-1}$	$NF_t - NF_{t-1}$	S_t	B_t
$F_{t-1} - F_{t-2}$	-.0312	.0349	2.1492	-1.0366
	(-.48)	(.27)	(3.09)***	(-.43)
$NF_{t-1} - NF_{t-2}$	-.0014	.0109	.3230	-.8704
	(-.06)	(.19)	(1.17)	(-.93)
S_{t-1}	-.0045	-.0010	.9668	.0543
	(-2.43)**	(-.25)	(33.78)***	(.75)
B_{t-1}	.0047	.0054	.0240	.4478
	(3.17)***	(1.49)	(1.50)	(6.68)***
$Rbar^2$	.05	-.01	0.92	0.20

Table 6: Sub-period VAR results

The table shows a VAR of the return to fundamentals (F_t - F_{t-1}) for the Hi-Lo portfolio, return to deviations from fundamentals (NF_t - NF_{t-1}) for the Hi-Lo portfolio, Baker-Wurgler sentiment, S, and bullish sentiment, B. Monthly data 1988.01 to 2011.01, divided at 2000.12. Stock returns each month are split between fundamental returns and deviations from fundamentals based on a regression of the stock return on the oil price return, gas price return, and the change in contango in the oil market, using a rolling window of 60 months prior to the month for which the stock return is split. Coefficient $\theta_{i,j}$ measures the autoregression coefficient of variable j on the lagged value of variable i. The system is estimated using GMM with Newey-West correction for the standard errors.   t-statistics in parentheses. * denotes 10% significance, ** 5% significance, and *** 1% significance.

	(1)	(2)	(3)
	1988-2011	1988-2000	2001-2011
Regression of fundamental return on lagged sentiment			
Baker-Wurgler sentiment: $\theta_{S,F}$	-.0045	-.0011	-.0059
	(-2.43) **	(-.41)	(-2.52) **
Bullish sentiment: $\theta_{B,F}$	.0047	.0022	.0069
	(3.17) ***	(1.21)	(2.60) ***
Rbar^2	.05	-.01	.08
Regression of deviations from fundamentals on lagged sentiment			
Baker-Wurgler sentiment: $\theta_{S,NF}$	-.0010	.0092	-.0046
	(-.25)	(1.29)	(-1.06)
Bullish sentiment: $\theta_{B,NF}$	.0054	.0018	.0049
	(1.49)	(.33)	(1.20)
Rbar^2	-.01	-.01	.01
Partial serial correlation coefficient of			
Baker-Wurgler sentiment: $\theta_{S,S}$	.9668	1.008	.9555
	(33.78) ***	(31.31) ***	(30.60) ***
Bullish sentiment: $\theta_{B,B}$	.4478	.3583	.4383
	(6.68) ***	(5.65) ***	(4.02) ***

Table 7: Effect of sentiment on returns using different measurement intervals

The table shows results from a VAR of the return to fundamentals ($F_t - F_{t-1}$) for the Hi-Lo portfolio, return to deviations from fundamentals ($NF_t - NF_{t-1}$) for the Hi-Lo portfolio, Baker-Wurgler sentiment (S), and Bullish sentiment (B). The differencing interval in months is shown in the left column. Monthly data 1988.-01 to 2011.01, divided at 2000.12. Stock returns each month are split between fundamental returns and deviations from fundamentals based on a regression of the stock return on the oil price return, gas price return, and the change in contango in the oil market, using a rolling window of 60 months prior to the month for which the stock return is split. The system is estimated using GMM with Newey-West correction for the standard errors. t-statistics in parentheses. * denotes 10% significance, ** 5% significance, and *** 1% significance.

Differencing interval (months)	Fundamentals			Deviations from fundamentals		
	$\theta_{S,F}$	$\theta_{B,F}$	Rbar^2	$\theta_{S,NF}$	$\theta_{B,NF}$	Rbar^2
Panel A: 1988-2011						
1	-.0045	.0047	.05	-.0010	.0054	-.01
	(-2.43) **	(3.17) ***		(-.25)	(1.49)	
3	-.0103	.0116	.15	-.0033	..0064	-.01
	(-2.61) ***	(3.64) ***		(-.26)	(.94)	
12	-.0482	.0271	.23	-.0212	-.0110	.02
	(-3.12) ***	(2.79) ***		(-.82)	(-.60)	
Panel B: 1988-2000						
1	-.0011	.0022	-.01	.0092	.0018	-.01
	(-.41)	(1.21)		(1.29)	(.33)	
3	-.0035	.0081	.14	.0241	-.0013	.02
	(-.61)	(2.41) **		(1.21)	(-.11)	
12	-.0449	.0157	.16	-.0465	.0286	.08
	(-1.76)	(1.83)		(-.98)	(1.15)	
Panel C: 2001-2011						
1	-.007	.0069	.08	-.0046	.0049	.01
	(-2.52) **	(2.60) ***		(-1.06)	(1.20)	
3	-.0154	.0163	.27	-.0074	.0061	-.00
	(-3.54) ***	(3.10)***		(-.57)	(.59)	
12	-.0648	.0241	.29	-.0034	-.0199	.06
	(-3.12) ***	(1.51)		(-.11)	(-.76)	

Table 8: Regression of changes in the oil price on "deep" fundamental factors and lagged sentiment (second period)

Panel A summarizes the results of a regression of changes in the price of WTI against two lagged sentiment measures, S_{t-1} and B_{t-1}, and controls for fundamental factors. Oil consumption is OECD consumption. Economic activity is US Industrial Production. The regressions consist of 121 rolling 12-month and 3-month changes. The regressions are estimated using OLS with a constant (not reported). Standard errors in the overlapping regressions are calculated using a Newey-West correction. t-statistics in parentheses. * denotes 10% significance, ** 5% significance, and *** 1% significance. Panel B shows the results of the same regressions without the deep fundamental controls and only the sentiment variables.

Panel A		
	Overlapping 12-month data (2001.01-2011.01) N= 121	Overlapping 3-month data (2001.01-2011.01) N = 121
Baker-Wurgler sentiment	-.017 (-0.42)	-.031 (-0.48)
Bullish sentiment	.291 (1.22)	.156 (1.23)
Δ world oil prod'n	3.52 (1.91)**	1.15 (.65)
Δ oil consumption	-3.01 (-2.31)**	-1.75 (-1.96)*
Δ economic activity	3.91 (4.96)***	3.85 (1.46)
Δ OECD oil stocks	-4.77 (-2.85)***	-2.59 (-2.46)**
Rbar^2	.60	.21
Panel B		
Baker-Wurgler sentiment	-.156 (-2.76)***	-.064 (-2.32)**
Bullish sentiment	.584 (1.47)	.249 (1.26)