JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 48, No. 1, Feb. 2013, pp. 245–275
COPYRIGHT 2013, MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON, SEATTLE, WA 98195
doi:10.1017/S0022109012000592

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

Cognitive Dissonance, Sentiment, and Momentum

Constantinos Antoniou, John A. Doukas, and Avanidhar Subrahmanyam*

Abstract

We consider whether sentiment affects the profitability of momentum strategies. We hypothesize that news that contradicts investors' sentiment causes cognitive dissonance, slowing the diffusion of such news. Thus, losers (winners) become underpriced under optimism (pessimism). Short-selling constraints may impede arbitraging of losers and thus strengthen momentum during optimistic periods. Supporting this notion, we empirically show that momentum profits arise only under optimism. An analysis of net order flows from small and large trades indicates that small investors are slow to sell losers during optimistic periods. Momentum-based hedge portfolios formed during optimistic periods experience long-run reversals.

I. Introduction

Does sentiment affect financial asset prices? This issue is enduring and has taken on renewed significance in the context of dramatic rises and falls in the stock market during this decade. We address this question by examining whether variations in profitability from a key pattern in stock prices, namely, stock price momentum, can be explained by variations in sentiment. Notably, our sentiment

* Antoniou, c.antoniou@exeter.ac.uk, Xfi Centre for Finance and Investment, University of Exeter Business School, Streatham Court, Rennes Dr, Exeter, EX4 4ST, UK; Doukas, jdoukas@odu.edu, Old Dominion University Graduate School of Business, Constant Hall Ste 2080, Norfolk, VA 23529, and Judge Business School, University of Cambridge; and Subrahmanyam, subra@anderson.ucla.edu, Anderson School of Management, University of California at Los Angeles, 110 Westwood Plz, Los Angeles, CA 90095. We thank an anonymous referee, Sridhar Arcot, Hendrik Bessembinder (the editor), Werner DeBondt, Andras Fulop, Stuart Gabriel, Soeren Hvidkjaer, Murali Jagannathan, Dennis Lasser, Ken Lehn, Laurence Lescourret, Haim Levy, Yee Cheng Loon, Dong Lou, Hanno Lustig, Marios Panayides, Richard Roll, Kristian Rydqvist, Steve Salterio, Eduardo Schwartz, Carmen Stefanescu, Geoff Tate, Shawn Thomas, Premal Vora, Neng Wang, and seminar participants at ESSEC, University of Pittsburgh, University of California at Los Angeles, Indira Gandhi Institute of Development Research, Indian Institute of Management (Kolkata), State University of New York-Binghamton, and the 2010 Asian Finance Conference in Hong Kong, as well as the 2nd Annual Research Symposium on Current Issues in Accounting and Finance at Brock University, for valuable comments, and the Conference Board for kindly providing us with the sentiment data. We also are grateful to Jeffrey Wurgler and Malcolm Baker for making their sentiment index publicly available. This paper was previously titled "Sentiment and Momentum."

proxy is measured outside of the financial markets, as we use the Consumer Confidence Index® published by the Conference Board (CB) (orthogonalized with respect to a set of macroeconomic variables).

The phenomenon of price momentum is documented in several studies (e.g., Jegadeesh and Titman (1993), (2001), Chan, Jegadeesh, and Lakonishok (1996)) and is well known to survive consideration of standard risk adjustments (Fama and French (FF) (1996)). This return pattern is found to be robust across different markets (Rouwenhorst (1998), Doukas and McKnight (2005)) and different asset classes (Asness, Moskowitz, and Pedersen (2009)). The highly debated explanations for price momentum range from time-varying expected returns (e.g., Johnson (2002)) to rationales based on market frictions and investor psychology (Hong and Stein (1999), Daniel, Hirshleifer, and Subrahmanyam (1998)).[1] We shed light on the latter class of arguments by examining the relationship between momentum-induced profits and sentiment.

Sentiment, broadly defined, refers to whether an individual, for whatever *extraneous* reason, feels excessively optimistic or pessimistic about a situation. A large body of the psychology literature finds that peoples' *current* sentiment affects their judgment of future events. For example, Johnson and Tversky (1983) show that people who read sad newspaper articles subsequently view various causes of death, such as disease, etc., as more likely than people who read pleasant newspaper articles. In general, the evidence indicates that people with positive sentiment make optimistic judgments and choices, whereas people with negative sentiment make pessimistic ones (Bower (1981), (1991), Arkes, Herren, and Isen (1988), Wright and Bower (1992), among others).

We augment the Hong and Stein (1999) arguments to establish a link between sentiment and momentum. Their framework indicates that news diffuses slowly through the actions of different sets of "newswatchers" that sequentially react to news, and this creates momentum. A class of "momentum traders" trades reflexively in response to past price movements. Some momentum traders mistake price movements due to previous momentum trades as fundamental news movements. Their reactive trades set off an overreaction that eventually is corrected as momentum positions are reversed. We hypothesize that "newswatchers" will underreact more strongly when they receive information that contradicts their sentiment due to cognitive dissonance (Festinger (1957)). This implies that bad (good) news among loser (winner) stocks will diffuse slowly when sentiment is optimistic (pessimistic). In turn, this will lead to momentum, albeit driven by the loser portfolio in optimistic sentiment periods and the winner portfolio in pessimistic sentiment periods. Although this argument alone predicts symmetric momentum across sentiment periods, as a practical matter momentum may

[1]Empirically, Hong, Lim, and Stein (2000) show that, controlling for firm size, momentum profits are decreasing in analyst coverage, thus supporting the notion that momentum is caused by slow information diffusion as suggested by the model of Hong and Stein (1999). Chordia and Shivakumar (2002) find that momentum profits are largely predictable from a set of macroeconomic variables, proposing a rational explanation for momentum. Cooper, Gutierrez, and Hameed (2004) find that momentum returns are entirely captured by lagged market returns, and suggest a behavioral explanation of momentum. For further discussions on the causes of momentum, see Conrad and Kaul (1998), Moskowitz and Grinblatt (1999), Grundy and Martin (2001), and Grinblatt and Han (2005).

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

be more pronounced when sentiment is optimistic because arbitraging cognitive dissonance in these states requires the costly short selling of loser stocks.

To ensure that our sentiment measure is free of macroeconomic influences, like Baker and Wurgler (2006), (2007), we conduct our investigation using the residual from the regression of the CB Index on a set of macroeconomic variables. Furthermore, in our robustness checks, we also consider the alternative index for investor sentiment constructed by Baker and Wurgler (2006), (2007). We find that when sentiment is optimistic, the 6-month momentum strategy yields significant profits, equal to an average monthly return of 2.00%. However, when investor sentiment is pessimistic, momentum profits decrease dramatically to an insignificant monthly average of 0.34%. Furthermore, we find that momentum in optimistic periods arises primarily from continuing underperformance of losers with bad news. This pattern is more pronounced when short-selling constraints are more binding.

Our basic result of strong momentum in optimistic periods and virtually no momentum in pessimistic periods survives a host of robustness checks, including controls for market returns, analyst coverage, and firm size. As controls for risk, we use a standard capital asset pricing model (CAPM), a FF (1993) approach, and a conditional version of the CAPM, where the betas are allowed to vary with sentiment, and find that our result survives all 3 methods.

To shed further light on the source of our results, we use intraday transactions data to estimate stock-by-stock order imbalances (OIBs) across optimistic and pessimistic periods, separately for large and small trades. Our analysis indicates that small investors are slow to sell losers during optimistic periods. This finding supports the argument that bad news causes cognitive dissonance among the smaller, naïve investors when they have optimistic beliefs. On the other hand, we find that large (and presumably more sophisticated) investors are net sellers of losing stocks in the formation periods of momentum portfolios, suggesting that they respond more promptly to negative information. Further analysis based on the responses of small and large investors to earnings surprises lends additional support to these conclusions.

We also find that investor sentiment provides an important link between short-run continuation and the long-run stock price reversal as predicted by the Hong and Stein (1999) model. Specifically, we examine the long-run behavior of optimistic and pessimistic momentum portfolios 5 years after portfolio formation and find that momentum profits reverse significantly after optimistic periods, with an average monthly return of –0.49%, whereas momentum profits after pessimistic periods do not.

In a related and significant paper, Cooper, Gutierrez, and Hameed (2004) suggest that investor biases will be more accentuated after market gains, and they show that momentum is profitable only after market increases. Our study partitions momentum profits on our sentiment measure, which is an exogenous proxy of agents' propensity to form erroneous beliefs. We confirm the results of Cooper et al. and show that sentiment has incremental power to explain momentum-induced profits after accounting for market returns. Chordia and Shivakumar (2002) show that momentum profits are only significant in periods in which the economy is expanding and attribute their finding to cyclical variation in expected

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

returns. These authors are careful, however, to point out that their finding does not rule out a sentiment-based explanation,[2] and by examining the relation between our (orthogonalized) sentiment measure and momentum, such a rationale is what we pursue.

Other recent literature shows important evidence that suggests that sentiment affects stock prices.[3] This has led several authors to explore the relationship between investor sentiment and various stock market anomalies. Thus, investor sentiment has been linked to the post-earnings announcement drift (Livnat and Petrovic (2008)), fund flows and the value effect (Frazzini and Lamont (2008)), corporate disclosure (Bergman and Roychowdhury (2008)), initial public offerings (IPOs) (Cornelli, Goldreich, and Ljungqvist (2006)), and the size effect (Baker and Wurgler (2006), (2007)). Our study fits into this literature by analyzing the relationship between investor sentiment and momentum, an important stock market anomaly.

The remainder of this paper is organized as follows: Section II describes the data and the empirical methodology. Section III presents the results, along with a discussion of the sensitivity analysis, robustness checks, and further examinations. Section IV concludes the paper.

II. Data and Methodology

We use all common stocks (share codes 10 and 11) listed in the New York and American Stock Exchanges (NYSE and AMEX, respectively) from the Center for Research in Security Prices (CRSP) monthly file. The sample time period is from Feb. 1967 to Dec. 2008, for which the CB Index is available.

We construct momentum portfolios using the methodology of Jegadeesh and Titman (1993). In each month t, we sort all stocks in decreasing order of their returns for the past J months. Based on these rankings, 10 equal-weighted portfolios are formed. The top decile is termed the "winners" portfolio, and the bottom decile is the "losers" portfolio. Every month, the strategy takes a long position in the winner portfolio and a short position in the loser portfolio, held for K months. We construct overlapping portfolios to increase the power of our tests. Specifically, we close the position initiated in month $t - K$ in both the winner and loser portfolios and take a new position using the winners and losers of month t. Therefore, in each month, we revise $1/K$ of the stocks in the winner and loser portfolios,

[2]Chordia and Shivakumar (2002) suggest that the challenge to this rationale would be to provide an explanation of why investors misinterpret macro information but not firm-specific information. Our sentiment-based argument provides such an explanation, since our notion is that optimism about the overall economy can alter the investment choice regarding individual companies.

[3]See, for example, Hirshleifer and Shumway (2003), who use sunshine to capture investors' mood, and confirm that returns are higher on sunnier days. Edmans, Garcia, and Norli (2007) capture mood using sporting events, and they find that after losses in international competitions, stock markets of losing nations fall. Charoenrook (2003), Brown and Cliff (2005), and Lemmon and Portniaguina (2006) use consumer confidence indices constructed from household surveys to proxy investors' sentiment, and they find that asset returns decline following periods of optimism. Baker and Wurgler (2006) create a sentiment index from market-based variables and arrive at similar conclusions.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

and carry over the rest from the previous month.[4] In order to avoid microstructure biases, we allow 1 month between the end of the formation period and the beginning of the holding period, and we delete all stocks that are priced less than $1 at the beginning of the holding period.

As mentioned earlier, for the main part of our analysis we measure investor sentiment using the monthly time series of consumer confidence sentiment constructed by the CB. This survey begins on a bimonthly basis in 1967 and converts to a monthly series in 1977.[5] The CB questionnaire, sent to 5,000 randomly selected households in the United States, asks participants 5 questions about their outlook for the economy.[6] The scores for each question are calculated as the number of favorable replies, divided by the sum of favorable and unfavorable replies. The scores on the 5 questions are amalgamated to form the overall Consumer Confidence Index. In previous research, the index is used to predict household spending activity (Acemoglu and Scott (1994), Ludvigson (2004)), as well as to proxy for investor sentiment (e.g., Lemmon and Portniaguina (2006), Fisher and Statman (2003)).

In order to purge the effects of macroeconomic conditions from the CB Index, we regress this monthly index on 6 macroeconomic indicators: growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and a National Bureau of Economic Research (NBER) recession indicator. We use the residuals from this regression as the sentiment proxy.[7]

To identify whether a particular formation period is optimistic or pessimistic, we calculate a weighted-rolling average of the sentiment level for the 3 months prior to the end of the formation period. We give a weight of 3 to sentiment in the prior month, 2 to the 1 in the month prior to that, and 1 to the month 3 months prior to the current month.[8,9] A formation period is classified as optimistic (pessimistic) if the 3-month rolling average ending in month t belongs in the top (bottom) 30% of the 3-month rolling average sentiment time series. In order to ensure that our

[4]For example, for the 6-month formation-holding-period strategy ($J, K = 6$), in each month $t + 1$, the winner portfolio is comprised of ⅙ (winners from $t-1$) + ⅙ (winners from $t-2$) + $\cdots$ + ⅙ (winners from $t - 6$), and correspondingly for the loser portfolio. Note that month t is skipped.

[5]For the period that the index is available on a bimonthly basis, we follow Qiu and Welch (2006) in using linear interpolation to obtain monthly observations.

[6]The questions are the following: i) How would you rate present general business conditions in your area? ii) What would you say about available jobs in your area right now? iii) Six months from now, do you think that the business conditions in your area will be better, same, or worse? iv) Six months from now, do you think there will be more, same, or fewer jobs available in your area? v) Would you guess your total family income to be higher, same, or lower 6 months from now?

[7]This sentiment indicator is also used by McLean and Zhao (2009).

[8]We classify the momentum portfolio, formed at the end of month t, as optimistic or pessimistic using the weighted average of the residual sentiment from the 3 previous months as follows: ⅜ $\times$ residual(t) + ⅜ $\times$ residual$(t-1)$ + ⅙ $\times$ residual$(t-2)$. This weighting scheme is chosen in order to assign more weight to the most recent sentiment observation when we predict momentum profits, and is similar to the one used in Lakonishok, Shleifer, and Vishny ((1994), p. 1550). However, our main results remain unchanged even when we use a simple arithmetic average.

[9]Since sentiment is announced with a 1-month delay, the use of residuals from month t, $t-1$, and $t-2$ to calculate the rolling sentiment measure actually corresponds to sentiment during months $t-1$, $t-2$, and $t-3$. We also consider alternative sentiment specifications based on 2- and 4-month lags and find that our results continue to hold.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

analysis is not sensitive to the definition of sentiment states, we also consider 20% and 40% cutoff points, and as reported later, the results are substantively similar.

Because we form overlapping portfolios, in each holding-period month we hold stocks from different formation periods, across which sentiment can differ. In order to calculate the average sentiment in these formation periods, we first calculate whether each of these formation periods is optimistic or pessimistic as explained above, and then we tally how many were optimistic or pessimistic. If all the formation periods are classified as optimistic (pessimistic), the particular holding-period month is classified as optimistic (pessimistic), with the rest being "mild" sentiment months.[10]

To test whether momentum profits in each sentiment state are equal to 0, we regress the time series of average monthly momentum profits on 3 dummy variables for OPTIMISTIC, MILD, and PESSIMISTIC sentiment, with no intercept. To test if mean profits in optimistic sentiment periods are different from profits in pessimistic sentiment periods, we regress average monthly momentum profits on MILD and OPTIMISTIC sentiment dummy variables, with a constant. This approach, which is similar to that of Cooper et al. (2004), helps preserve the full time series of returns and allows us to estimate *t*-statistics that are robust to autocorrelation and heteroskedasticity using Newey and West (1987) standard errors.

Later in the paper, we also calculate the long-run performance of the momentum portfolios, focusing on the 6-month formation-holding-period strategy. For that analysis, we follow the methodology employed by Jegadeesh and Titman (2001), whereby for each momentum portfolio constructed, we define an event date that is 13 months following the initial formation date.[11] After this date, we hold the portfolio for 5 years and test whether portfolios formed in optimistic formation periods behave differently from those formed after pessimistic periods.

Table 1 presents descriptive statistics for our sentiment index. Panel A is based on the raw data of consumer confidence provided by the CB. Panel B reports the 3-month rolling average using the residuals from regressing the raw CB data on a set of macroeconomic variables. The raw CB Index, as shown in Figure 1, rises during the late 1960s, mid 1980s, and late 1990s, and it falls during the 1970s and early 1990s. These patterns are in line with the evidence for investor sentiment discussed by Baker and Wurgler (2006). The decline in sentiment for the period 2006–2008 seems to be an early sign of the recent recession. As shown in Figure 1, the 3-month rolling-weighted average of this residual, which is the

[10]For example, assuming $J = K = 6$, in June 1980 we hold stocks selected from 6 ranking periods ending in May, April, March, February, and January. For each of the 6 ranking periods, we calculate the sentiment level in the previous 3 months and classify each formation period as being high, mild, or low sentiment.

[11]Thus, for instance, the portfolio held in June 1980 is initiated in Nov. 1979 (skipping Dec.). This portfolio is based on overlapping returns, thus it is an equal-weighted portfolio of the positions initiated in January, February, March, April, and June. For this portfolio, the post-holding period starts in Jan. 1981, after which we continue to hold the same portfolio using the equal-weighted structure for a period of 5 years.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

sentiment measure used in our main analysis, tracks the raw CB index closely (i.e., shows an upward trend when the index is rising and vice versa).[12]

TABLE 1

Descriptive Statistics

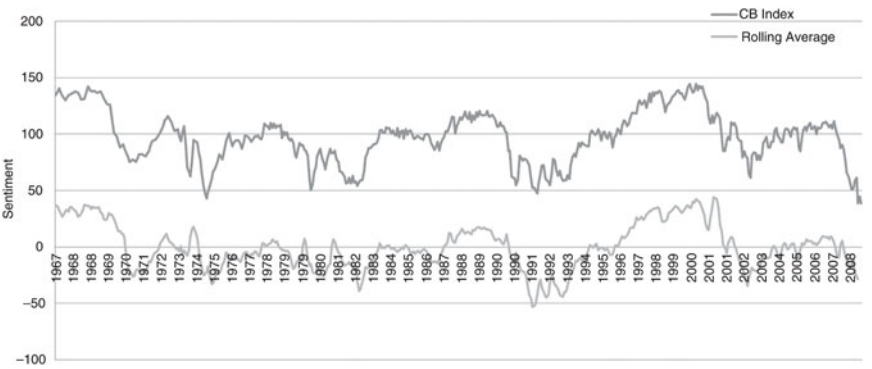
Panel A of Table 1 presents descriptive statistics for the raw time series of consumer confidence, as compiled by Conference Board (CB). Panel B presents the 3-month rolling average of the component of investor sentiment that is orthogonal to macroeconomic conditions. To derive this component we regress raw sentiment on growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator, and then use the residuals from this regression to calculate the 3-month rolling average. The sample period is Apr. 1967–Dec. 2008.

Mean	σ	Q1	Median	Q3	Minimum	Maximum	N
Panel A. CB Consumer Confidence							
97.40	23.06	82.59	98.00	110.60	38.62	144.71	501
Panel B. CB Consumer Confidence Orthogonal to Macroeconomic Variables							
−0.06	19.96	−13.13	−1.32	11.91	−52.89	44.13	501

FIGURE 1

Investor Sentiment (CB) (1966–2008)

Figure 1 plots 2 series. The 1st series is the raw data of consumer confidence provided by the Conference Board (CB). The 2nd series is the 3-month rolling average of the residual from regressing the CB index series on the following set of macroeconomic variables: growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and an NBER recession indicator.



A robust finding in the literature is that investor sentiment is reflected in the size premium (Lee, Shleifer, and Thaler (1991), Baker and Wurgler (2006), (2007), Lemmon and Portniaguina (2006)). The usual interpretation of this finding is that optimistic investors are drawn to small stocks, thereby reducing the size premium in the following period. In order to validate our sentiment proxy, we regress the 3-month average residual sentiment ending in month t on the FF (1993) SMB portfolio return in month $t + 1$.[13] We obtain a coefficient of −0.023 (t-value = −3.16) on SMB, which corroborates our sentiment proxy.

[12]The fact that the orthogonalization does not materially affect the behavior of the index is in line with the findings of Baker and Wurgler (2006).

[13]We thank Ken French for the SMB data (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

III. The Hypothesis and Empirical Evidence on Momentum Profits across Sentiment States

Our central hypothesis is that sentiment may influence momentum by way of cognitive dissonance. The argument builds upon Hong and Stein (1999), who indicate that momentum arises due to slow diffusion of news. We propose that negative (positive) information about stocks when sentiment is optimistic (pessimistic) will conflict with investors' prior beliefs and thus cause cognitive dissonance. As a result, information opposed to the direction of sentiment will diffuse particularly slowly and cause momentum.

Although the preceding argument alone implies a symmetric momentum effect in optimistic and pessimistic sentiment periods, previous research suggests that it may be more pronounced in optimistic sentiment periods. Specifically, because of limits to arbitrage, it would be more difficult for arbitrageurs to exploit cognitive dissonance in optimistic periods, as this entails costly short selling in loser stocks (D'Avolio (2002)), whereas arbitraging cognitive dissonance in pessimistic states only requires buying winners. This observation suggests that momentum may not be symmetric across optimistic and pessimistic sentiment states.

A. Investor Sentiment and Short-Run Momentum Profits

Our 1st empirical test examines the profitability of the momentum strategy conditioning on pessimistic and optimistic investor sentiment states. Table 2 presents the results for strategies that are based on a 6-month ranking period (J) and holding periods (K) of 3, 6, and 12 months sorted by investor sentiment. In Panel A (Panel B) pessimistic sentiment is defined as the bottom 30% (40%) of the rolling average sentiment time series.[14]

Table 2 demonstrates that momentum profits are sensitive to our sentiment measure. Thus, in Panel A2, for the $J = K = 6$ strategy, average monthly profits in optimistic periods are highly significant at 2.00%; they decrease to 1.46% per month in mild sentiment months, and shrink to a statistically insignificant 0.34% in months with pessimistic sentiment.[15] When the holding period is extended to 12 months ($J = 6$, $K = 12$) in Panel A3, average monthly profits in optimistic (mild) periods are 1.27% (0.85%), while they decline to 0.09% in pessimistic periods. Similarly, when the holding period is condensed to 3 months ($J = 6$, $K = 3$) in Panel A1, average monthly profits in optimistic (mild) periods are 2.27% (1.44%), declining to an insignificant 0.29% in pessimistic periods. Comparable results are shown in Panel B, confirming that the choice of cutoff point for optimistic and pessimistic sentiment does not materially affect our conclusions.

[14]Using a 20% cutoff for optimistic/pessimistic sentiment yields similar results that are not reported for brevity, but are available from the authors.

[15]The unconditional momentum strategy for the period 1966–2008, based on J, $K = 6$, yields an average monthly profit of 1.38% (an unreported result). This figure is comparable with studies of momentum for analogous time periods (Lee and Swaminathan (2000), Jegadeesh and Titman (2001)).

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 2

Momentum Profits Conditional on Investor Sentiment

Table 2 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks for the time period Apr. 1967–Dec. 2008. At the beginning of each month all stocks are ranked based on their cumulative returns over the previous J months. Portfolio 1 includes the loser stocks, and Portfolio 10 the winner stocks. The winner stocks are bought and the loser stocks sold, and this position is held for K months. Monthly holding period returns come from overlapping strategies and are computed as an equal-weighted average of returns from strategies initiated at the beginning of this month and the previous $K - 1$ months. We allow 1 month between the end of the formation period and the beginning of the holding period, and we delete all stocks that are priced less than $1 at the beginning of the holding period. Sentiment is measured using the time series of consumer confidence sentiment index constructed by the Conference Board. We regress this series on growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator, and we use the residuals from this regression as the sentiment proxy. In order to identify whether a particular formation period was optimistic or pessimistic, in each month t we calculate the average sentiment level for the previous 3 months, using a weight of 3⁄6 for month t, a weight of 2⁄6 for month $t-1$, and a weight of 1⁄6 for month $t-2$. In Panel A (Panel B) the top 30% (40%) observations of this rolling average time series are the high-sentiment periods, and the bottom 30% (40%) the low-sentiment periods. To identify each holding-period month as optimistic and pessimistic, we calculate how many of the K formation periods were of high and low sentiment. If all K formation periods were classified as optimistic (pessimistic), the holding-period month is classified as optimistic (pessimistic). To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. The t-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to $K - 1$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel A. 30%–30% Sentiment States													
Panel A1. J = 6, K = 3													
OPTIMISTIC	($n = 133$)	−0.85	−0.05	0.36	0.53	0.68	0.78	0.96	0.90	1.09	1.42	2.27	[5.06]
MILD	($n = 246$)	−0.24	0.53	0.81	0.91	0.97	1.01	1.04	1.04	1.14	1.20	1.44	[4.67]
PESSIMISTIC	($n = 121$)	1.86	2.07	2.21	2.14	2.08	1.97	1.91	1.84	1.89	2.15	0.29	[0.56]
											Opt. – Pes.	1.98	[2.90]
Panel A2. J, K = 6													
OPTIMISTIC	($n = 121$)	−0.48	0.17	0.52	0.67	0.86	0.95	1.10	1.10	1.26	1.51	2.00	[5.66]
MILD	($n = 286$)	−0.28	0.34	0.63	0.77	0.86	0.91	0.99	1.05	1.12	1.18	1.46	[5.66]
PESSIMISTIC	($n = 93$)	2.12	2.41	2.45	2.31	2.24	2.21	2.11	2.13	2.21	2.45	0.34	[0.77]
											Opt. – Pes.	1.66	[2.96]
Panel A3. J = 6, K = 12													
OPTIMISTIC	($n = 109$)	−0.27	0.20	0.49	0.62	0.78	0.86	0.94	0.96	1.00	1.00	1.27	[3.50]
MILD	($n = 337$)	0.38	0.75	0.95	1.02	1.10	1.12	1.18	1.22	1.25	1.23	0.85	[4.14]
PESSIMISTIC	($n = 54$)	2.05	2.25	2.21	2.12	2.11	2.05	2.00	2.00	2.06	2.14	0.09	[0.22]
											Opt. – Pes.	1.18	[2.20]
Panel B. 40%–40% Sentiment States													
Panel B1. J = 6, K = 3													
OPTIMISTIC	($n = 172$)	−1.51	−0.53	−0.07	0.12	0.29	0.39	0.57	0.52	0.65	0.87	2.38	[6.09]
MILD	($n = 170$)	0.24	0.91	1.16	1.27	1.31	1.33	1.35	1.35	1.42	1.48	1.24	[2.97]
PESSIMISTIC	($n = 158$)	1.63	1.88	2.00	1.94	1.89	1.81	1.75	1.71	1.83	2.08	0.45	[1.05]
											Opt. – Pes.	1.93	[3.33]
Panel B2. J, K= 6													
OPTIMISTIC	($n = 149$)	−0.99	−0.23	0.17	0.36	0.58	0.68	0.85	0.90	1.05	1.26	2.25	[6.83]
MILD	($n = 227$)	0.05	0.65	0.93	1.05	1.08	1.11	1.15	1.18	1.24	1.26	1.21	[4.12]
PESSIMISTIC	($n = 124$)	1.56	1.82	1.89	1.82	1.83	1.85	1.80	1.85	1.93	2.21	0.65	[1.83]
											Opt. – Pes.	1.60	[3.29]
Panel B3. J = 6, K = 12													
OPTIMISTIC	($n = 124$)	−0.65	−0.08	0.24	0.38	0.57	0.66	0.76	0.79	0.82	0.80	1.45	[3.91]
MILD	($n = 304$)	0.50	0.83	1.04	1.11	1.18	1.20	1.26	1.30	1.32	1.31	0.81	[3.71]
PESSIMISTIC	($n = 72$)	1.96	2.13	2.06	1.95	1.93	1.89	1.84	1.84	1.89	2.00	0.04	[0.14]
											Opt. – Pes.	1.41	[2.87]

We also observe from Table 2 that the higher momentum profits in optimistic periods arise primarily because loser stocks continue to underperform in subsequent periods. This indicates that bad news diffuses slowly when investors are optimistic. In pessimistic periods, momentum does not obtain because both

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

winner and loser stocks earn positive holding-period returns of roughly the same order of magnitude, thus negating the return spread between winning and losing deciles. This is consistent with the notion that the arbitraging of cognitive dissonance in pessimistic states (which requires buying winners) is effective in enforcing market efficiency across winners and losers in pessimistic states.[16] (We will shed more light on this issue in Sections H and I.) An interesting aside, which is not the focus of our paper, but deserves attention in future research, is that the post-formation period returns of *all* deciles are higher after pessimistic formation periods than after optimistic ones.[17]

The finding that momentum profits are significant in "mild" sentiment months is in line with extant experimental literature in decision making, which consistently documents that *on average*, subjective beliefs are more optimistic than objective probabilities (e.g., Slovic (2000), Puri and Robinson (2007)).[18] Our evidence lends support to these studies, as we show that "mild" sentiment states entail some excessive optimism, giving rise to significant momentum profits, which increase (decrease) substantially when sentiment becomes more optimistic (pessimistic).

As stated earlier, these results corroborate the analysis of Chordia and Shivakumar (2002) and Cooper et al. (2004), who respectively find that momentum profits vary significantly according to whether the market has been rising or falling or whether the economy has been expanding or contracting. Going further, however, our analysis explicitly links the time series of momentum profits to sentiment. Our analysis accords with the general notion that the profitability of the momentum trading style is susceptible to significant time variation, since the returns of the winner and the loser portfolios do not preserve their spread across optimistic and pessimistic sentiment states.[19]

In Sections III.B–III.F we examine the robustness of the evidence that momentum profits are only significant during periods of optimistic sentiment. Unless

[16]If managers themselves disclose good news promptly to boost their stock prices in pessimistic periods, as shown by Bergman and Roychowdhury (2008), then good news will be propagated quickly, counteracting the cognitive dissonance of investors toward good news in times of pessimism. This phenomenon may also reduce the performance of winners in the holding period, thus contributing to decreased momentum.

[17]The finding is consistent with the notion that in periods of pessimism, investors are less inclined to take on risk, and thus set stock prices lower in pessimistic formation periods, so that future returns are high following these periods (Baker and Wurgler (2006)). In additional analysis we calculate the average price-earnings (P/E) ratios of each portfolio at the end of the formation period and find that they are lower (and statistically different) in pessimistic periods than in optimistic ones (unreported result). This finding also suggests that stocks generally become undervalued in pessimistic formation periods. The positive returns in the 3- to 12-month holding periods following pessimistic formations are consistent with Veldkamp (2005), who argues that the paucity of information in times of pessimism (because of low investment activity) causes a "slow boom" (gradual rise in stock prices) during the ensuing periods.

[18]Various studies examine the microeconomic foundations of average optimism in beliefs. Brunnermeier and Parker (2005) suggest that it is a consequence of anticipatory utility, and Bracha and Brown (2010) that it is a consequence of affective decision making.

[19]In unreported analysis, we examine whether sentiment captures variation in momentum profits on the portfolio level, as documented by Lewellen (2002) (25 size and book-to-market portfolios and 17 industry portfolios). Our results continue to hold as these portfolios generate significant momentum in optimistic sentiment periods, but not in pessimistic sentiment periods. This suggests that our results, like Lewellen's, are not driven by firm or industry-specific returns.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

stated otherwise, we analyze the 6-month formation- and holding-period strategy ($J = 6$, $K = 6$) and define sentiment as in Panel A of Table 2.[20]

B. Investor Sentiment, Momentum, and Market States

Cooper et al. (2004) test whether the momentum profits are related to past market returns. They identify UP and DOWN market states using the returns of the market for a 36-month period prior to the beginning of the strategy's holding period. If this return is positive (negative), they classify the market state as UP (DOWN). Then they compute momentum profits after UP and DOWN markets. Their results indicate that momentum profits are significant only after UP markets. To address how our results relate to Cooper et al., we classify each formation period into UP or DOWN market states independent of investor sentiment. We calculate the CRSP value-weighted index return (including dividends) for the 36-month (Panels A1 and B1 of Table 3), 24-month (Panels A2 and B2), and 12-month (Panels A3 and C3) period just prior to the strategy's holding period. If this return is positive (negative), we classify the market state as UP (DOWN). We then derive momentum profits for optimistic and pessimistic periods during UP (Panel A) and DOWN (Panel B) markets.

TABLE 3

Momentum Profits Conditional on Different Market States and Investor Sentiment

Table 3 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks for the time period Apr. 1967–Dec. 2008. Panel A gives momentum strategies implemented in UP markets, whereas Panel B gives momentum strategies implemented after DOWN markets. The state of the market is the return of the value-weighted market index including dividends 36 (Panels A1, B1), 24 (Panels A2, B2), and 12 (Panels A3, B3) months prior to the beginning of the holding period, as measured by Cooper et al. (2004). We allow 1 month between the end of the formation period and the holding period, and we delete all stocks that are priced less than $1 at the beginning of the holding period. Sentiment is defined as in Table 2. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel A. UP Markets													
Panel A1. 36-Month Market													
OPTIMISTIC	($n = 113$)	−0.60	0.11	0.48	0.63	0.82	0.90	1.05	1.08	1.24	1.52	2.12	[4.73]
MILD	($n = 254$)	−0.27	0.39	0.70	0.83	0.95	1.00	1.06	1.14	1.22	1.28	1.55	[5.18]
PESSIMISTIC	($n = 69$)	1.15	1.74	1.88	1.80	1.75	1.73	1.61	1.62	1.74	2.01	0.87	[1.51]
											Opt. – Pes.	1.25	[1.72]
Panel A2. 24-Month Market													
OPTIMISTIC	($n = 103$)	−0.75	−0.02	0.36	0.54	0.75	0.82	0.98	1.01	1.18	1.45	2.21	[4.86]
MILD	($n = 252$)	−0.34	0.37	0.69	0.83	0.95	1.01	1.09	1.18	1.29	1.40	1.74	[6.01]
PESSIMISTIC	($n = 76$)	1.50	1.94	2.00	1.91	1.86	1.84	1.74	1.74	1.89	2.16	0.66	[1.25]
											Opt. – Pes.	1.55	[2.22]
Panel A3. 12-Month Market													
OPTIMISTIC	($n = 87$)	−0.50	0.30	0.71	0.85	1.08	1.15	1.34	1.42	1.62	2.03	2.53	[6.16]
MILD	($n = 206$)	0.06	0.69	0.93	1.00	1.09	1.12	1.17	1.24	1.36	1.49	1.43	[5.36]
PESSIMISTIC	($n = 86$)	1.81	2.22	2.29	2.16	2.11	2.10	2.01	2.01	2.14	2.42	0.61	[1.49]
											Opt. – Pes.	1.92	[3.29]

(continued on next page)

[20]Defining sentiment as in Panel B of Table 2 yields very similar results, which are available from the authors.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 3 (continued)

Momentum Profits Conditional on Different Market States and Investor Sentiment

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel B. DOWN Markets													
Panel B1. 36-Month Market													
OPTIMISTIC	($n = 8$)	1.20	0.95	1.00	1.31	1.43	1.57	1.80	1.39	1.53	1.46	0.26	[0.10]
MILD	($n = 32$)	−0.36	−0.11	0.02	0.37	0.22	0.24	0.38	0.35	0.29	0.40	0.76	[0.60]
PESSIMISTIC	($n = 24$)	4.91	4.33	4.09	3.78	3.65	3.60	3.55	3.59	3.55	3.72	−1.20	[−0.82]
											Opt. – Pes.	1.46	[0.50]
Panel B2. 24-Month Market													
OPTIMISTIC	($n = 18$)	1.06	1.27	1.40	1.44	1.49	1.66	1.79	1.59	1.71	1.87	0.80	[0.45]
MILD	($n = 34$)	0.17	0.11	0.18	0.38	0.21	0.19	0.25	0.05	−0.19	−0.45	−0.62	[−0.48]
PESSIMISTIC	($n = 17$)	4.88	4.52	4.47	4.11	3.93	3.86	3.77	3.86	3.65	3.75	−1.12	[0.61]
											Opt. – Pes.	1.92	[0.75]
Panel B3. 12-Month Market													
OPTIMISTIC	($n = 34$)	−0.45	−0.16	0.03	0.22	0.32	0.43	0.49	0.27	0.33	0.18	0.63	[0.47]
MILD	($n = 80$)	−1.17	−0.58	−0.15	0.20	0.27	0.38	0.52	0.57	0.50	0.37	1.54	[1.74]
PESSIMISTIC	($n = 7$)	5.95	4.67	4.42	4.15	3.81	3.60	3.41	3.54	3.02	2.86	−3.09	[−1.03]
											Opt. – Pes.	3.72	[1.13]

These results are reported in Table 3. From Panels A1 and B1 it can be seen that out of the 500 holding-period months in the sample, 436 (87.2%) occur in UP markets and only 64 (12.8%) in DOWN markets. Interestingly, in UP market states, we find considerable variation in investor sentiment, as 69 periods (or 16%) are classified as pessimistic, 254 (or 58%) as mild, and 113 (or 26%) as optimistic.

Momentum strategies in DOWN markets, as shown in Panel B of Table 3, generally produce insignificant momentum profits, regardless of investor sentiment. However, the number of observations in each sentiment group is very small and, therefore, these results do not allow meaningful interpretation. Momentum profits in UP markets, as Panel A of Table 3 shows, vary with investor sentiment. Specifically, in Panel A1 (36-month market return), momentum profits in optimistic periods are highly significant at a monthly average of 2.12%. This average decreases to 1.55% in mild sentiment months, and to an insignificant 0.87 (t-value = 1.51) in pessimistic months. Similar, but stronger, results are reported in Panels A2 (24-month market return) and A3 (12-month market return). These results are consistent with our previous findings, which show that momentum profits are significantly larger when investor sentiment is optimistic. One noteworthy finding is that loser portfolios in DOWN markets experience large positive returns (reversals), even though the winner-loser differential in these cases is not significant.

In Table 4 we report regression results based on the regression model of Cooper et al. ((2004), Tab. V, p. 1361), augmented with investor sentiment. Specifically, we estimate the following model (omitting time subscripts):

$$(1) \quad \text{PROFITS} = b_0 + b_1\text{SENTIMENT} + b_2\text{MARKET} + b_3\text{MARKET}^2 + u.$$

The variable PROFITS is the time series of average monthly momentum profits in month t. In the regression, SENTIMENT is defined as the 3-month weighted-rolling average of the sentiment residual ending in month $t - 1$. MARKET is the

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

lagged market return of the value-weighted index including dividends during the 12- (Part 1), 24- (Part 2), and 36- (Part 3) month periods prior to the beginning of the strategy's holding period. $MARKET^2$ is the square of the market return.

TABLE 4

Regressions of Momentum Profits on Market Returns and Investor Sentiment

Table 4 presents regressions based on the regression model of Cooper et al. ((2004), Tab. V, p. 1361), augmented with investor sentiment. MARKET is the return of the value-weighted market index 36, 24, and 12 months prior to the beginning of the holding period, and $MARKET^2$ is the square term of the MARKET. SENTIMENT is the 3-month weighted-rolling average ending in month $t-1$ divided by 1,000. In Panel C, we define the sentiment residual by regressing raw sentiment in month t on the macroeconomic variables and market returns (12-month returns in Part 1, 24-month in Part 2, and 36-month in Part 3). The dependent variable is momentum profits in month t. The t-statistics are calculated using Newey-West (1987) standard errors, where the lag is set to $K-1$. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Part 1: 12-Month Market Return			Part 2: 24-Month Market Return			Part 3: 36-Month Market Return		
Parameter		Est.	t-Stat.	Adj. R^2	Est.	t-Stat.	Adj. R^2	Est.	t-Stat.	Adj. R^2
Panel A. Cooper et al. Regression with SENTIMENT: Mom. PROFITS $= b_0 + b_1 SENTIMENT + b_2 MARKET + b_3 MARKET^2 + u$										
Constant	b_0	0.014	5.03	1.80%	0.0143	4.76	3.06%	0.011	3.39	3.34%
SENTIMENT	b_1	0.327	3.33		0.309	3.37		0.272	2.95	
MARKET	b_2	0.061	1.69		0.083	2.37		0.109	3.53	
$MARKET^2$	b_3	−0.447	−1.52		−0.470	−2.53		−0.378	−3.36	
Panel B. Regression with Market Returns and SENTIMENT: Mom. PROFITS $= b_0 + b_1 MARKET + b_2 SENTIMENT + u$										
Constant	b_0	0.012	4.39	1.60%	0.01	2.99	1.87%	0.008	2.29	1.96%
SENTIMENT	b_1	0.338	3.39		0.300	3.15		0.270	2.86	
MARKET	b_2	0.047	1.44		0.046	1.74		0.043	2.00	
Panel C. Cooper et al. Regression (as in Panel A) with SENTIMENT Orthogonal to Market Returns										
Constant	b_0	0.014	5.04	1.82%	0.013	4.46	2.92%	0.010	2.98	3.26%
SENTIMENT	b_1	0.328	3.34		0.297	3.21		0.264	2.80	
MARKET	b_2	0.060	1.67		0.094	2.66		0.122	3.98	
$MARKET^2$	b_3	−0.448	−1.53		−0.469	−2.51		−0.380	−3.36	

Panel A of Table 4 reports the results from the regression of Cooper et al. (2004) augmented with sentiment and shows that momentum profits increase with the market return but decrease with the squared market term, indicating a nonlinear relationship and confirming the results of Cooper et al. (2004).[21] The results also show that the coefficient of SENTIMENT is positive and significant across all market return specifications (12, 24, and 36 months). Specifically, in Panel A1, when we use a 12-month lagged market return, the coefficient on SENTIMENT is equal to 0.327 with a t-value of 3.33. When we use the 24-month lagged market return (Panel A2) the coefficient is 0.309 with a t-value of 3.37, and when we use the 36-month lagged market return (Panel A3) it is equal to 0.272 with a t-value of 2.95. In addition, the results show that the effect of MARKET on momentum decreases when market returns are calculated over shorter time periods. For the 36-month period, the coefficient on MARKET is 0.109 with t-value 3.53 and decreases to a mildly significant 0.061 with a t-value of 1.69 for the 12-month period. Interestingly, while these results display that SENTIMENT

[21] In unreported analysis (available from the authors) we run a regression identical to that of Cooper et al. (2004) (without the sentiment variable) and find results similar to theirs.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

predicts momentum profits independently of market returns, they also show that it is a stronger predictor when the market return is calculated over shorter periods.

In Panel B of Table 4 we run the regression without the squared market term to compare the economic impacts of MARKET and SENTIMENT on momentum profits. Using the sample standard deviations of the 2 variables and the regression coefficients, in unreported analysis, we find that when the 36-month market return is used, a 1-standard-deviation increase in SENTIMENT implies an increase in average monthly momentum profits of 0.54%, whereas an analogous move in MARKET has an impact on momentum profits of 0.47%. For the regression involving the 24-month MARKET, the corresponding magnitudes are 0.60% and 0.50%, and for the 12-month MARKET, they are 0.67% and 0.51%, respectively.

In Panel C of Table 4 we completely de-link our sentiment measure from market effects by using a sentiment measure that is orthogonal to market returns and macroeconomic variables. To obtain this measure we regress raw sentiment on market returns (12-month market returns in Panel C1, 24-month in Panel C2, and 36-month in Panel C3) and macroeconomic variables and use the residuals from this regression to calculate SENTIMENT.[22] The results show that SENTIMENT is positive and significant in the 3 specifications of the market return.[23] Overall, the results in Tables 3 and 4 show that after controlling for market states, investor sentiment captures material variation in momentum profits.

C. Is It an Analyst Coverage or a Size Effect?

A large literature suggests that return predictability is stronger for smaller companies, which are held mostly by individual investors (Nagel (2005)), and entail higher arbitrage costs (D'Avolio (2002), Jegadeesh and Titman (1993), (2001)). Further, Hong et al. (2000) show that momentum is stronger for stocks with low analyst coverage, because lower analyst following slows the diffusion of news. In this section, we explore whether our previous results, reported in Table 2, depend on the size or analyst coverage of the company.

Table 5 presents results for the sample stratified by analyst following. We use the number of Institutional Brokers' Estimate System (IBES) analysts making 1-year-ahead earnings per share (EPS) forecasts as a proxy for analyst coverage, and term this variable ANALYSTS. We then match ANALYSTS in month t with the CRSP market capitalization (SIZE) at the end of the month $t-1$. As in Hong et al. (2000), in order to isolate the role of analyst following vis-à-vis size, we perform the monthly cross-sectional regression $\log(1+\text{ANALYSTS}) = a + b \times \log(\text{SIZE}) + e$. Then, in each month, we form 3 equal-sized samples in increasing order of the residuals (e).[24] Panels A, B, and C document the momentum profits for the low-, mid-, and high-residual coverage stocks, respectively.

[22]The correlations between SENTIMENT and MARKET in this regression are small (less than 0.07 in absolute terms) in all 3 panels, illustrating that the process of calculating the 3-month rolling-weighted average does not induce correlation between the variables.

[23]A version of the regression in Panel C of Table 4 for only UP market states yields substantively similar results.

[24]Following Hong et al. (2000), analyst coverage is matched to firms in the momentum portfolios 6 months prior to the beginning of the formation period.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 5

Momentum Profits Conditional on Investor Sentiment and Analyst Coverage

Table 5 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks for the time period Jan. 1980–Dec. 2008. Panels A–C give momentum strategies implemented on the companies with low, medium, and high analyst coverage. To stratify the sample, we first perform the cross-sectional regression $\log(1+\text{ANALYSTS}) = a + b \times \log(\text{SIZE}) + e$, where ANALYSTS is the number of analysts making 1-year-ahead EPS forecasts in each month t, and SIZE is the market capitalization at the end of the month $t-1$. Then, we form 3 groups of analyst coverage every month using the residuals (e) from the above model. We allow 1 month between the end of the formation period and the holding period, and we delete all stocks that are priced less than $1 at the beginning of the holding period. Sentiment is defined as in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. The t-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to $K-1$. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy − Sell	[t-Stat.]
Panel A. Low Coverage (mean = 2.57 analysts)													
OPTIMISTIC	($n = 77$)	−0.94	0.05	0.65	0.79	0.86	0.98	1.04	0.96	1.15	1.26	2.19	[4.32]
MILD	($n = 200$)	−0.83	0.12	0.45	0.66	0.85	0.94	0.97	1.04	1.08	1.20	2.03	[6.62]
PESSIMISTIC	($n = 71$)	1.56	2.20	2.24	2.16	2.03	2.11	1.84	1.94	2.13	2.05	0.49	[0.92]
											Opt. – Pes.	1.70	[2.37]
Panel B. Mid Coverage (mean = 6.48 analysts)													
OPTIMISTIC	($n = 77$)	−0.48	0.41	0.79	0.78	1.02	0.97	1.03	1.08	1.17	1.53	2.01	[4.28]
MILD	($n = 200$)	−0.43	0.25	0.65	0.80	0.94	1.01	1.04	1.09	1.07	0.93	1.35	[4.31]
PESSIMISTIC	($n = 71$)	2.11	2.18	2.25	2.15	2.07	1.98	2.01	1.97	2.01	2.46	0.35	[0.70]
											Opt. – Pes.	1.66	[2.44]
Panel C. High Coverage (mean = 10.42 analysts)													
OPTIMISTIC	($n = 77$)	−0.17	0.51	0.67	0.78	0.93	0.97	1.21	1.24	1.28	1.66	1.83	[3.37]
MILD	($n = 200$)	−0.36	0.33	0.64	0.67	0.82	0.89	0.91	0.99	1.10	1.30	1.66	[5.20]
PESSIMISTIC	($n = 71$)	2.42	2.51	2.48	2.23	2.29	2.21	2.08	2.06	2.16	2.43	0.02	[0.03]
											Opt. – Pes.	1.81	[2.26]

As can be seen from Table 5, the difference in momentum profits between optimistic and pessimistic periods is very similar across the 3 groups, and momentum profits during pessimistic periods are insignificant throughout. Note that returns of extreme losers are lower (more negative) for low-coverage stocks during nonpessimistic periods. While we have verified that these differences are not statistically significant, the point estimates are consistent with the Hong et al. (2000) notion that low coverage slows the diffusion of news, causing stronger momentum. Overall, the sentiment effect documented in Table 2 is robust to analyst coverage, as the effect of sentiment on momentum profits is preserved across all the coverage groups.

Next, we use the size breakpoints on Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html) to construct deciles by market capitalization. We then apply our momentum strategy separately to companies in the 5 smaller firm groups and the other 5 groups. These results are reported in Table 6 and show that sentiment affects momentum for both small and large stocks. For small stocks (Panel A), we observe that momentum profits in optimistic periods decline from 2.14% to 1.72% in mild sentiment periods and to an insignificant 0.46% in pessimistic periods. The corresponding figures for large companies are 0.86%, 0.81%, and 0.26%.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 6

Momentum Profits Conditional on Investor Sentiment and Firm Size

Table 6 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks for the time period Apr. 1967–Dec. 2008. This table gives momentum strategies implemented on the companies in the smaller 5 size deciles (Panel A) and the larger 5 size deciles (Panel B). SIZE is measured as price × shares outstanding at the end of the formation period. Size decile breakpoints are from Kenneth French's data library. We allow 1 month between the end of the formation period and the holding period, and we delete all stocks that are priced less than $1 at the beginning of the holding period. Sentiment is defined as in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. The *t*-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to $K - 1$. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel A. Small Market Capitalization													
OPTIMISTIC	(n = 121)	−0.67	0.07	0.36	0.62	0.84	0.90	1.08	1.11	1.28	1.47	2.14	[6.16]
MILD	(n = 286)	−0.48	0.20	0.54	0.74	0.89	0.99	1.06	1.16	1.24	1.23	1.72	[6.48]
PESSIMISTIC	(n = 93)	2.13	2.51	2.65	2.65	2.55	2.51	2.48	2.52	2.52	2.58	0.46	[0.88]
											Opt. – Pes.	1.68	[2.69]
Panel B. Large Market Capitalization													
OPTIMISTIC	(n = 121)	0.35	0.60	0.73	0.85	0.78	0.87	0.96	0.86	1.05	1.21	0.86	[2.17]
MILD	(n = 286)	0.22	0.55	0.69	0.75	0.80	0.77	0.81	0.86	0.96	1.03	0.81	[3.05]
PESSIMISTIC	(n = 93)	1.80	1.87	1.87	1.91	1.80	1.64	1.67	1.62	1.72	2.07	0.26	[0.60]
											Opt. – Pes.	0.60	[1.01]

Our evidence that momentum is generally larger for smaller companies confirms the findings of Jegadeesh and Titman (1993), (2001). Furthermore, the evidence that the effect of sentiment is much more dramatic in smaller companies (an average monthly return differential in the amount of 1.68% vis-à-vis 0.60% for large companies) supports the argument of Baker and Wurgler (2006) that the influence of sentiment tends to be more pronounced in the smaller companies that are harder to value and hence more prone to subjective evaluations. This finding is also consistent with Hong and Stein (1999), who argue that news about small firms diffuses more slowly because investors face larger fixed costs of information acquisition in these firms, and thus uncover relevant news less speedily than in large firms.

D. Is It Risk?

While the evidence so far suggests that conditioning on investor sentiment has a dramatic impact on the profits of momentum strategies, we have not addressed the possibility that the higher (lower) returns of the winner (loser) portfolio during periods of optimism load more (less) strongly on economic risk factors. We now tackle this issue by estimating CAPM-, FF- (1993), and conditional CAPM- (CCAPM-) adjusted momentum returns across different sentiment states.

In accordance with Cooper et al. (2004), we perform the risk adjustment by forming a time series of raw momentum returns corresponding to each event month of the holding period. Specifically, to form CAPM- and FF- (1993)

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

risk-adjusted profits, for each holding-period month, portfolio returns are regressed on the appropriate factors and a constant. In this manner, we obtain estimated factor loadings for each portfolio and holding-period month, which we use to derive risk-adjusted profits as follows:

$$r_{kt}^{\mathrm{ADJ}} = r_{kt} - \sum_{t} \beta_{ik} f_{it}, \tag{2}$$

where r_{kt} represents the raw returns of each momentum portfolio for the strategy in the holding-period month K, in calendar month t, f_{it} is the realization of factor i in calendar month t, and β_{ik} is the estimated factor loading in month K on f_{it}. We use the excess return of the value-weighted market index, R_m, over the 1-month T-bill return, R_f as the market portfolio in the CAPM, and the return differential between small and big companies (SMB) and high and low book-to-market companies (HML) for the FF (1993) risk adjustment.

The previous models rely on the assumption that the covariance of momentum portfolio returns with the risk factors is constant. If this is not the case, as discussed in Grundy and Martin (2001), a more appropriate test would be to condition betas on sentiment in order to control for the possibility that the patterns we document reflect sentiment-related time-varying systematic risk. To do this we use a CCAPM-based robustness check, where we allow the covariance between the returns of momentum portfolios with the excess market return to vary with investor sentiment. Specifically, we estimate risk-adjusted returns using the following model:

$$r_{kt}^{\mathrm{ADJ}} = r_{kt} - \left(\beta_{ik} - \beta_{ik}^{\mathrm{SENT}} \times \mathrm{SENTIMENT}_{t-j}\right)(R_m - R_f), \tag{3}$$

where r_{kt} represents the raw returns of each momentum portfolio for the strategy in the holding-period month K in calendar month t, β_{ik} is the estimated factor loading in month K on the excess market return, and $\beta_{ik}^{\mathrm{SENT}}$ is the factor loading in month K on the interaction between the excess market return and investor sentiment during the formation period.[25] The time-varying betas argument predicts that the covariance between momentum profits and excess market returns increases when sentiment is optimistic; therefore, returns increase accordingly to compensate for the increased covariation.

Table 7 gives the CAPM, FF (1993), and CCAPM-adjusted momentum profits. The pattern of momentum profits in Table 2 remains robust to these risk adjustments. Momentum profits are highly significant, at monthly averages of 2.03% (CAPM), 2.08% (FF (1993)), and 2.03% (CCAPM) when the strategy is implemented in optimistic investor sentiment periods. However, in pessimistic periods, momentum profits drop remarkably to a monthly average return of 0.48% (CAPM), 0.96% (FF (1993)), and 0.47% (CCAPM). Note that the CAPM and the CCAPM-adjusted returns are virtually indistinguishable, suggesting that beta is not materially related to investor sentiment. This result is in line with the analysis of Baker and Wurgler (2006).

[25] Because we perform overlapping strategies for each portfolio return observation, we have CB residuals from K formation periods. In equation (3), SENTIMENT is the average sentiment from these K formation periods.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 7

Risk-Adjusted Momentum Profits Conditional on Investor Sentiment

Table 7 presents risk-adjusted momentum profits calculated from CAPM, FF (1993), and conditional CAPM (CCAPM) models. For each momentum portfolio and holding-period month we form a time series of returns, which we regress on excess market return when we risk adjust according to the CAPM, and excess market return, the SMB and HML factors when we risk adjust according to the FF (1993) 3-factor model. For the CCAPM we allow beta to differ depending on the average sentiment in the 6 formation periods that correspond to each portfolio return observation (see equation (3)). Using these loadings and the factor realizations in each month, we estimate the monthly excess return for each portfolio. The data on market returns, the risk-free rate, and the SMB and HML factors are from Kenneth French's data library. Sentiment is defined as in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. The *t*-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to $K - 1$. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel A. CAPM													
OPTIMISTIC	($n = 121$)	−0.83	−0.13	0.24	0.41	0.61	0.69	0.85	0.84	0.98	1.20	2.03	[5.46]
MILD	($n = 286$)	−0.52	0.14	0.44	0.60	0.69	0.75	0.82	0.87	0.93	0.97	1.49	[5.93]
PESSIMISTIC	($n = 93$)	0.72	1.22	1.34	1.25	1.22	1.20	1.10	1.09	1.11	1.21	0.48	[1.10]
											Opt. – Pes.	1.55	[2.68]
Panel B. FF													
OPTIMISTIC	($n = 121$)	−0.87	−0.25	0.10	0.26	0.47	0.55	0.71	0.72	0.90	1.21	2.08	[5.39]
MILD	($n = 286$)	−0.82	−0.14	0.19	0.35	0.47	0.53	0.61	0.67	0.74	0.80	1.61	[6.83]
PESSIMISTIC	($n = 93$)	−0.46	0.18	0.39	0.36	0.39	0.42	0.33	0.35	0.40	0.51	0.96	[2.30]
											Opt. – Pes.	1.12	[1.95]
Panel C. Conditional CAPM													
OPTIMISTIC	($n = 121$)	−0.83	−0.12	0.25	0.41	0.61	0.70	0.85	0.84	0.99	1.20	2.03	[5.46]
MILD	($n = 286$)	−0.52	0.13	0.43	0.59	0.68	0.74	0.81	0.87	0.92	0.96	1.48	[5.92]
PESSIMISTIC	($n = 93$)	0.64	1.09	1.19	1.09	1.06	1.04	0.95	0.95	0.98	1.11	0.47	[1.07]
											Opt. – Pes.	1.56	[2.70]

Overall, while we cannot rule out every possible risk-based explanation of our findings, it is reasonable to conclude that the performance of momentum strategy in periods of optimistic investor sentiment is not explicable by rational risk premia as modeled in standard settings, namely, the CAPM, the conditional CAPM, and the Fama and French (1993) framework.

E. Is the CB Sentiment Index Forecasting Future Macroeconomic Conditions?

Although traditional risk-based models do not appear to account for the sentiment effect on momentum profits, this effect may still be related to some form of rational pricing if our sentiment measure reflects future macroeconomic activity, which determines holding-period returns. In this section we construct our sentiment measure by controlling for proxies for future macroeconomic conditions. Specifically, we replicate the analysis in Panel A of Table 2 by orthogonalizing the CB index to current macroeconomic indicators (described in Section II), their 1-quarter-ahead values,[26] and the closing value of the volatility index (VIX) at the

[26]The current value of the NBER recession dummy variable is used.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

end of the month in which sentiment is measured. The inclusion of the 1-quarter-ahead macroeconomic variables allows us to control for future macroeconomic conditions. We include VIX as a proxy for macroeconomic expectations, since it is obtained primarily as a consequence of trading by sophisticated options investors (Lakonishok, Pearson, and Poteshman (2007)).[27] All of the other calculations remain unaltered, with the difference that the sample period of this test is shorter, as VIX is available from Jan. 1985.[28]

Table 8 reports results for $J = K = 6$. (Results for other J, K combinations considered in Table 2 are not reported for brevity but are qualitatively similar.) As can be seen, the results remain essentially unchanged even when we orthogonalize the CB index with respect to future macroeconomic conditions and VIX. For example, momentum profits in optimistic sentiment states are highly significant at a monthly average of 2.42%. They decline to 1.51% in mild sentiment periods and to an insignificant 0.27% in pessimistic periods. These findings suggest that our patterns in momentum profits do not arise simply because our sentiment measure forecasts future macroeconomic activity.

TABLE 8

Momentum Profits Conditional on Sentiment Orthogonal to Current, Future Macroeconomic Conditions, and VIX

Table 8 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks for the time period Jan. 1985–Dec. 2008. The description of the momentum strategy is defined in Table 2. Sentiment is measured using the time series of consumer confidence sentiment index constructed by the Conference Board. We regress this series on growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, an NBER recession indicator, 1-quarter-ahead growth in industrial production, durable, nondurable, and services consumption, and employment and the closing level of the VIX at the last day of the month in which sentiment is measured. We use the residuals from this regression as the sentiment proxy. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. The *t*-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to $K - 1$. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
OPTIMISTIC	($n = 54$)	−1.44	−0.47	0.06	0.27	0.48	0.52	0.72	0.68	0.84	0.98	2.42	[4.34]
MILD	($n = 167$)	−0.53	0.26	0.58	0.68	0.79	0.86	0.88	0.88	0.90	0.99	1.51	[4.73]
PESSIMISTIC	($n = 51$)	1.88	1.88	1.82	1.73	1.69	1.66	1.61	1.67	1.82	2.15	0.27	[0.43]
											Opt. – Pes.	2.15	[2.52]

[27] For a general discussion of VIX (the index options-based VIX), see Whaley (2009). The level of the VIX may also be related to sentiment, as shown by Kaplanski and Levy (2010). However, since options are primarily traded by sophisticated investors, it is reasonable to assume that the sentiment displayed by the VIX is not as dramatic as that displayed by the CB index. Therefore, we suppose that at least some of the variability in the VIX is related to expectations about future macroeconomic conditions.

[28] The computation of VIX was based on Standard & Poor's (S&P) 100 index options until Sept. 19, 2003, and subsequently on S&P 500 index options. Whaley ((2009), fn. 9), suggests a method by which the VIX computation based on S&P 100 index options is adjusted to account for the slightly lower volatility of the S&P 500 index. The unadjusted and adjusted versions of VIX give identical results; we report results using the unadjusted series.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

F. An Alternative Sentiment Index

In this section, we examine the sensitivity of our results to an alternative index for investor sentiment, which is the measure constructed by Baker and Wurgler (2006), (2007).[29] These authors suggest that investor sentiment can be captured by variables that relate to investors' propensity to purchase stock. They construct a time series of sentiment using 6 proxies: trading volume (measured as total NYSE turnover), the premium for dividend-paying stocks, the closed-end fund discount, the number of IPOs as well as the mean 1st-day IPO return, and the equity share in new issues. Because these variables are partly related to economic fundamentals, they regress each against growth in industrial production, real growth in durable consumption, nondurable consumption, services consumption, growth in employment, and an NBER recession indicator. Their sentiment index is the 1st principal component of the residual series from the regressions.

Table 9 reports Table 2-equivalent momentum results for optimistic and pessimistic periods, using the Baker and Wurgler (2007) sentiment measure in place of our CB index. All other calculations remain the same as those in Table 2, with the difference that in this table we combine periods of mild and optimistic sentiment. We do this for brevity since these sentiment states yield very similar momentum profits,[30] and we gain some statistical power by combining the periods; moreover, as discussed in Section III.A, significant momentum profits in

TABLE 9

Momentum Profits Conditional on an Alternative Investor Sentiment Index

Table 9 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks for Oct.1965–Dec.2007. The momentum strategy is defined in Table 2. Sentiment is measured using the monthly sentiment index constructed by Baker and Wurgler (2007), using trading volume (measured as total NYSE turnover), dividend premium, closed-end fund discount, number and 1st-day returns in IPOs, and the equity share in new issues. Because these variables are partly related to economic fundamentals, Baker and Wurgler (2007) regress each proxy against growth in industrial production, real growth in durable, nondurable, and services consumption, growth in employment, and an NBER recession indicator, and they use the residuals from this regression as the sentiment proxies. The overall sentiment index is the 1st principal component of the 6 sentiment proxies. In order to identify whether a particular formation period was optimistic or pessimistic, we follow the same procedure as that outlined in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment and we group the MILD sentiment and OPTIMISTIC sentiment categories together. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on an OPTIMISTIC sentiment dummy variable and a PESSIMISTIC sentiment dummy variable, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on an OPTIMISTIC sentiment dummy variable with a constant. The *t*-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to $K - 1$. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
OPTIMISTIC	($n = 387$)	−0.18	0.47	0.76	0.88	0.98	1.04	1.1	1.14	1.25	1.4	1.59	[7.69]
PESSIMISTIC	($n = 120$)	2.31	2.34	2.29	2.21	2.11	2.04	2.1	2.15	2.28	2.61	0.30	[0.21]
											Opt. – Pes.	1.29	[2.86]

[29]This index is available from Jeffrey Wurgler's Web site (http://pages.stern.nyu.edu/∼jwurgler/).

[30]When $J = 6$, $K = 3$ ($J = 6$, $K = 12$) the corresponding momentum profits in optimistic periods are 1.71% (0.97%), reducing to an insignificant 0.23% (–0.01%) in pessimistic periods. When momentum profits are partitioned to 3 sentiment categories, and $J, K = 6$, the optimistic and mild sentiment categories yield average momentum profits of 1.40% and 1.67%, respectively. The corresponding numbers for $K = 3$ and $K = 12$ are 1.54% and 1.80%, and 0.70% and 1.05%.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

mild sentiment states imply investor optimism in these states as well. The evidence in Table 9 confirms our general relation between momentum profits and sentiment. Specifically, where $J, K = 6$, the results show that momentum profits in optimistic and mild periods amount to a monthly average of 1.59%, whereas in pessimistic periods they drop to an insignificant 0.30%.[31] Similar results are obtained for the other J, K combinations in Table 2. These findings corroborate our previous results.

G. Cognitive Dissonance and Momentum Profits

The evidence in the previous sections shows that momentum is stronger in optimistic sentiment periods, and that this is mainly driven by continued underperformance in the loser portfolio. Our augmented version of the Hong and Stein (1999) theory indicates that this is caused by cognitive dissonance toward negative news during optimistic periods. In this section we conduct a more direct test of this conjecture by examining the market's response to negative earnings surprises for loser stocks, conditional on sentiment. We first identify winners and losers, based on 6-month cumulative returns ending in month t, and we examine the pricing of earnings surprises in month $t + 1$. We then use the seasonal random walk model to compute standardized unexpected earnings (SUE). In each year-quarter all firms are ranked into deciles according to their SUE, with the top 30% firms classified as being the "good news" firms and the bottom 30% as the "bad news" firms. We calculate cumulative returns in the "impact" (days –1, 1 relative to the earnings announcement) and the "adjustment" period (days 2, 60) to examine whether sentiment affects the speed with which the earnings information is priced. For brevity, we only report results for loser stocks with negative earnings surprises; other results are available from the authors.

Table 10 reports the results. The short-term reactions shed light on the arguments of Veronesi (1999). He shows that in optimistic periods, negative news indicates a greater chance of a negative state (which drops the price), but also increased uncertainty as the probability of the good state moves below the upper bound of unity (which drops the price still further). In pessimistic periods, bad news does lower the probability of a good state (which drops the price) but also *decreases* uncertainty because the probability of the good state moves toward the lower bound of 0 (which has a countervailing effect on the price). So the negative reaction of prices to bad news in good states is greater than the reaction of prices to bad news in bad states. As we see in Table 10, the short-term absolute reaction for negative earnings during optimistic periods is higher than that for pessimistic periods, confirming the Veronesi argument.

Our momentum-related arguments, however, apply more to the price reactions in the longer term (i.e., column 3 in Panel A of Table 10). Consistent with the predictions of our hypothesis, we observe that the post-earnings announcement drift after negative surprises is much stronger when sentiment is optimistic, as the average cumulative return in the adjustment period is 11% lower. This result, which accords with Livnat and Petrovits (2008), suggests that the market

[31] We obtain very similar results when we use 40%–40% or 20%–20% cutoffs for sentiment states.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 10

Earnings Announcements and Momentum

Panel A of Table 10 presents cumulative abnormal returns for the (–1, 1) and (2, 60) intervals around negative earnings surprises for loser stocks. In each month t of the sample, we rank stocks in deciles based on their cumulative return in the past 6 months and retain the companies in the bottom decile. We delete stocks priced less than \$1 at the end of month t. Sentiment is the 3-month rolling average of the residual defined in Table 2 ending in month t and the different sentiment states are identified using 30% cutoff points. We identify companies with an earnings announcement in month $t + 1$ and perform an event study to examine the post-earnings announcement drift. We use the seasonal random walk model to compute earnings expectations, whereby the standardized unexpected earnings (SUE) is calculated as $\text{EARNINGS}_t - \text{EARNINGS}_{t-4}$/(QUARTER_END_PRICE). QUARTER_END_PRICE is the stock price at the end of quarter t. In each year-quarter all firms are ranked into deciles according to their SUE. The bottom 30% are the negative surprise firms. We report cumulative (raw) returns for losers with negative earnings surprises for the periods (–1, 1) and (2, 60), where date 0 is the earnings announcement date (note that the days correspond to trading days). Data on quarterly earnings announcements are from Compustat. The t-statistics in Panel A are calculated using clustered standard errors on the company level. Panel B presents average monthly momentum returns following the methodology in Table 2. In Panel B1 we report momentum returns when all stocks are included in the sample and in Panel B2 when we delete stocks in the loser portfolio with a negative earnings surprise (bottom 30% SUE) in the 1st 4 months of the holding period. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept using Newey-West (1987) standard errors, where the lag is set to $K - 1$. In Panel B the numbers of months in the pre- and post-formation periods are $J, K = 6$.

			Horizon		
Sentiment State			(−1, 1)		(2, 60)
Panel A. Post-Earnings Announcement Drift for Loser Stocks with Low SUE					
OPTIMISTIC			−1.72		−2.08
MILD			−1.61		1.29
PESSIMISTIC			−1.11		8.65
OPTIMISTIC – PESSIMISTIC			−0.62		−10.73
[t-statistic]			[−2.26]		[−12.73]
Sentiment State		Losers	Winners	Profits	[t-Stat.]
Panel B. Momentum Profits					
Panel B1. All Stocks					
OPTIMISTIC	($n = 77$)	−0.44	1.49	1.93	[4.17]
MILD	($n = 280$)	−0.19	1.17	1.36	[5.25]
PESSIMISTIC	($n = 100$)	2.89	2.48	−0.55	[−0.64]
Panel B2. Excluding Losers with Low SUE					
OPTIMISTIC	($n = 77$)	0.57	1.49	0.92	[2.34]
MILD	($n = 280$)	0.44	1.17	0.73	[3.18]
PESSIMISTIC	($n = 100$)	3.37	2.48	−1.03	[−1.34]

underreacts to adverse information that contradicts the prevailing optimistic sentiment.

In Panel B of Table 10 we examine the effect of the above phenomenon on momentum profits. We repeat the analysis in Panel A2 of Table 2 by first using all stocks (Panel B1), and then excluding losers with negative earnings surprises (Panel B2).[32] The results show that, once the latter stocks are excluded, average momentum profits in optimistic periods drop remarkably, from 1.93% to 0.92% per month. Conversely, when we exclude winners with positive earnings surprises momentum profits in optimistic periods drop to 1.55% per month (unreported result). This suggests that momentum profits in optimistic sentiment periods are primarily driven by cognitive dissonance toward bad news in the loser portfolio, as predicted by our hypothesis. In mild sentiment periods the contribution of loser stocks to momentum profits is dampened, which is expected since cognitive dissonance in these periods is weaker.

[32]In Panel A of Table 10 the figures are slightly different from those in Table 2 because the sample in this table is the intersection of CRSP and Compustat.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

Overall, the analysis in this section provides further support to our hypothesis that momentum in optimistic sentiment periods is driven by cognitive dissonance among loser stocks.

H. Cognitive Dissonance, Short Sale Constraints, and Momentum Profits

Our argument is that cognitive dissonance slows the reaction to bad news in good periods, causing momentum. We also argue that owing to short-selling constraints, this muted reaction is not corrected in a timely way. This argument implies that the underreaction in loser stocks due to cognitive dissonance should be more pronounced when short-selling constraints are likely to be more binding. In this section we test this proposition. We use 3 measures of short-selling constraints, namely institutional ownership, option listing status, and disagreement (D'Avolio (2002)). Stocks with higher levels of institutional ownership are more likely to have a supply of shares available for ready shorting. Furthermore, options, which allow for the establishment of bullish and bearish bets with equal ease, are likely to allay short-selling constraints. Finally, analyst disagreement implies that the stock might be overpriced (retail investors might buy on the extreme positive opinions but few will short). D'Avolio argues that this increases demand for shorting by the sophisticated investors, thus making short-selling constraints bind to a greater extent. We use the method in Table 6 and document momentum returns across optimistic, mild, and pessimistic periods, dividing stocks into those with high and low values of the proxies for short-sale constraints (SSC). These results are shown in Table 11.

For institutional ownership (Panel A of Table 11) the results show that average monthly momentum profits are higher in optimistic periods among the low institutional ownership stocks than high institutional ownership ones (2.39% vs. 1.54%). In addition, these higher profits are driven mostly by loser stocks, since the difference between the performance of losers in the low and high institutional ownership stocks is –1.37%, compared to –0.53% for the winners. The same pattern is observed in Panels B and C when we use option listing status and dispersion in analysts' forecasts in place of institutional ownership. In optimistic periods, momentum profits are higher for stocks with no options available (2.30% vs. 1.27%) and for those with high disagreement (2.35% vs. 1.01%), and are driven primarily by loser stocks. We perform a *t*-test for whether the profits of high SSC stocks are greater than those for low SSC stocks during optimistic and mild periods. We find that the unreported *p*-value for this test is smaller than 10% in all cases and smaller than 5% in all cases but one (Panel B during optimistic periods). Thus, in summary, the results in this section illustrate that the effect of cognitive dissonance on momentum profits is stronger among stocks where limits to arbitrage are more severe due to more stringent short-selling constraints.

I. Cognitive Dissonance and Investor Size

There is an abundance of evidence in the literature that imperfect reactions to new information, like the one we posit due to cognitive dissonance, are more

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

TABLE 11

Short-Selling Constraints and Momentum

Table 11 presents average monthly returns in percentages for price momentum strategies involving all NYSE/AMEX stocks partitioned according to sentiment and short sale cost proxies. The top half of Panel A gives momentum strategies implemented on the companies in the smaller 5 institutional ownership deciles, and the bottom half in the larger 5. Institutional ownership is measured using data from Thomson Reuters on WRDS at the end of the formation period, and the breakpoint is obtained using NYSE stocks. The sample period is Mar. 1980–Dec. 2008. In Panel B, momentum strategies are implemented separately for stocks with and without listed options. To obtain option listing status we use the first and last date that the company has data on traded options in the OptionMetrics database, and we check whether the portfolio formation period falls in this interval. The sample period is Jan. 1996–Dec. 2008. Finally, Panel C presents the results of momentum strategies implemented as in Panel A, with dispersion in analysts' forecasts as the relevant variable in place of institutional ownership. Dispersion is calculated as the standard deviation of the fiscal year 1 earnings forecasts divided by the absolute mean value, as reported in the IBES summary files. The breakpoint is obtained using NYSE stocks and the sample period is Nov. 1975–Dec. 2008. We allow 1 month between the end of the formation period and the holding period, and we delete all stocks that are priced less than $1 at the beginning of the holding period. Sentiment and *t*-statistics are calculated as in Table 2. In this table the numbers of months in the pre- and post-formation periods are $J, K = 6$.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel A. By Institutional Ownership													
Low Institutional Ownership													
OPTIMISTIC	($n = 74$)	−1.09	−0.09	0.40	0.70	0.79	0.84	1.04	1.09	1.14	1.30	2.39	[5.67]
MILD	($n = 147$)	−1.07	0.06	0.42	0.64	0.86	0.87	0.99	1.12	1.07	1.10	2.17	[7.05]
PESSIMISTIC	($n = 75$)	1.81	2.13	2.18	2.28	2.12	2.17	2.03	2.02	2.15	2.44	0.62	[1.18]
											Opt. – Pes.	1.77	[2.63]
High Institutional Ownership													
OPTIMISTIC	($n = 74$)	0.28	0.72	0.84	0.81	0.93	1.00	1.10	1.18	1.24	1.83	1.54	[2.64]
MILD	($n = 147$)	−0.19	0.39	0.54	0.86	0.89	0.93	0.90	1.02	1.07	1.25	1.44	[4.41]
PESSIMISTIC	($n = 75$)	1.88	2.03	1.93	2.02	1.79	1.81	1.79	1.68	1.80	2.04	0.16	[0.31]
											Opt. – Pes.	1.38	[1.76]
Panel B. By Options Listing Status													
No Listed Options													
OPTIMISTIC	($n = 58$)	−0.86	−0.13	0.48	0.66	0.79	0.88	0.98	1.03	1.14	1.44	2.30	[5.06]
MILD	($n = 85$)	−1.39	−0.52	−0.10	0.15	0.40	0.41	0.53	0.64	0.47	0.40	1.79	[4.68]
PESSIMISTIC	($n = 11$)	4.55	3.26	3.20	3.10	2.92	2.86	3.13	3.59	3.54	2.36	−2.20	[−1.38]
											Opt. – Pes.	4.50	[2.72]
With Listed Options													
OPTIMISTIC	($n = 58$)	0.79	0.96	1.02	0.96	1.01	1.17	1.23	1.24	1.38	2.06	1.27	[1.61]
MILD	($n = 85$)	−0.57	−0.21	−0.04	0.21	0.24	0.24	0.29	0.37	0.40	0.57	1.14	[2.33]
PESSIMISTIC	($n = 11$)	5.92	4.54	3.90	3.50	3.15	3.14	2.97	2.88	2.76	3.14	−2.78	[−1.49]
											Opt. – Pes.	4.05	[2.00]
Panel C. By Disagreement													
High Disagreement													
OPTIMISTIC	($n = 77$)	−0.57	0.54	0.68	0.75	0.84	0.86	1.12	1.11	1.23	1.78	2.35	[4.41]
MILD	($n = 246$)	−0.36	0.24	0.47	0.61	0.77	0.80	0.86	0.97	1.11	1.29	1.65	[5.00]
PESSIMISTIC	($n = 71$)	1.88	2.23	2.30	2.18	2.09	2.10	2.05	1.88	1.85	2.14	0.26	[0.40]
											Opt. – Pes.	2.09	[2.46]
Low Disagreement													
OPTIMISTIC	($n = 77$)	0.46	0.94	0.99	1.10	1.07	1.16	1.19	1.15	1.34	1.47	1.01	[2.23]
MILD	($n = 246$)	0.41	0.83	0.96	0.99	1.06	1.04	1.08	1.10	1.20	1.36	0.95	[4.77]
PESSIMISTIC	($n = 71$)	1.77	1.99	1.97	1.98	1.77	1.71	1.69	1.76	1.79	2.12	0.35	[0.63]
											Opt. – Pes.	0.67	[0.94]

likely to manifest themselves in the trading patterns of smaller, less sophisticated, investors (Odean (1999), Grinblatt and Keloharju (2009)). Existing evidence also suggests that large institutional investors process a larger information set and make superior trades (Malmendier and Shanthikumar (2007)). In this section, we analyze small and large investor net OIB in the loser portfolio conditional on sentiment, to examine whether cognitive dissonance is primarily a trait of small investors.

We follow Hvidkjaer (2006), (2008) in constructing order flow proxies for large and small investors and calculate the averages of these quantities for each

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

momentum portfolio in each month of the formation and holding periods.[33] Since computing OIB requires transactions data, which are not available for the entire sample period, the analysis spans the period 1983–2008. Results appear in Table 12.[34]

TABLE 12

OIBs for Momentum Portfolios

Table 12 presents the average monthly OIB in percentages in each formation- and holding-period month, for the loser and winner momentum portfolios. The sample period is 1983–2008. We follow Hvidkjaer's (2006), (2008) methodology to match trades to quotes, and to classify trades into 3 investor categories (small, medium, and large). We calculate the small and large trade imbalances for small and large investors. We subtract from this imbalance the marketwide imbalance for small or large investors on that day. We average this net imbalance for each month and company to derive a monthly measure of imbalance. We then form momentum portfolios as before. We then calculate average small and large investor imbalance for the loser and winner portfolio in each of the 6 months during the formation and holding periods, for OPTIMISTIC, MILD, and PESSIMISTIC periods. In this table we only report results for OPTIMISTIC and PESSIMISTIC periods. Sentiment is defined as in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. The *t*-statistics are in square brackets.

	Formation-Period Month						Holding-Period Month					
Sentiment State	−6	−5	−4	−3	−2	−1	1	2	3	4	5	6
Panel A. Optimistic												
A1. Small Investors												
Losers	2.78	3.19	2.85	2.48	1.79	0.54	0.66	−1.34	−2.22	−2.53	−3.2	−4.3
[*t*-stat.]	[2.76]	[3.47]	[3.07]	[2.81]	[2.08]	[0.63]	[0.6]	[−1.22]	[−1.95]	[−2.04]	[−2.76]	[−3.94]
Winners	−2.28	−1.65	−1.23	−0.97	−0.92	0.16	−0.58	0.83	1.48	2.15	2.43	2.78
[*t*-stat.]	[−3.12]	[−2.04]	[−1.49]	[−1.18]	[−1.11]	[0.20]	[−0.83]	[1.21]	[2.07]	[3.31]	[3.81]	[4.61]
A2. Large Investors												
Losers	−7.34	−7.02	−6.58	−6.51	−6.11	−5.25	−3.32	−3.31	−2.96	−2.45	−2.25	−1.95
[*t*-stat.]	[−7.62]	[−7.59]	[−7.12]	[−7.29]	[−6.87]	[−6.16]	[−3.27]	[−3.11]	[−2.71]	[−2.12]	[−1.88]	[−1.62]
Winners	2.63	2.65	2.99	3.14	3.02	2.74	−1.06	−1.35	−1.6	−1.34	−0.78	−0.56
[*t*-stat.]	[3.48]	[3.47]	[3.83]	[3.99]	[3.78]	[3.4]	[−1.38]	[−1.75]	[−2.11]	[−1.71]	[−0.99]	[−0.70]
Panel B. Pessimistic												
B1. Small Investors												
Losers	0.81	0.60	0.78	0.32	−0.66	−2.07	−0.15	−1.78	−2.81	−3.46	−4.03	−4.3
[*t*-stat.]	[0.94]	[0.74]	[0.96]	[0.43]	[−0.92]	[−3.13]	[−0.17]	[−2.06]	[−3.13]	[−4.07]	[−4.72]	[−4.56]
Winners	−2.16	−1.92	−2.08	−2.10	−1.79	−0.34	−1.89	−0.78	−0.12	−0.02	0.2	0.45
[*t*-stat.]	[−2.25]	[−2.22]	[−2.46]	[−2.56]	[−2.19]	[−0.40]	[−2.52]	[−1.1]	[−0.16]	[−0.02]	[0.24]	[0.56]
B2. Large Investors												
Losers	−1.39	−0.59	0.14	0.65	1.41	1.65	3.79	4.52	5.13	5.64	6.38	6.59
[*t*-stat.]	[−1.54]	[−0.63]	[0.16]	[0.71]	[1.43]	[1.68]	[3.53]	[3.98]	[4.65]	[5.08]	[5.62]	[5.85]
Winners	9.5	9.78	9.89	9.77	10.12	9.84	5.9	6.22	6.24	6.11	6.31	6.6
[*t*-stat.]	[7.38]	[7.59]	[7.65]	[7.3]	[7.3]	[7.23]	[4.86]	[5.46]	[5.58]	[5.36]	[5.67]	[6.14]

As can be seen in Panel A1 of Table 12, small investor order flow for the loser portfolio during optimistic periods is positive and significant in 5 of 6 months in the formation period, and it turns negative only in the holding period. This supports the argument that unsophisticated investors are slow to sell losers during optimistic periods, prolonging the pricing of bad news. On the contrary, large investors are net sellers of losing stocks in the formation period, suggesting that they

[33]The method involves sorting stocks into size-based quintiles and computing the 99th stock price percentile. Small trades are defined as trades whose dollar values are less than 100 times this percentile, and large trades are defined as those exceeding 200 times the percentile. Imbalances are market adjusted by subtracting the market-wide aggregate imbalance for each trade category. See Hvidkjaer (2006) for details.

[34]For brevity, we do not report results for the mild periods, which are available from the authors.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

respond to negative information for loser stocks. Large investors also exert some selling pressure on loser stocks in the holding period. It is unlikely, however, that this deferred selling pressure arises from underreaction because large investors sell losers more strongly during the formation period (i.e., for each event month the magnitude of the selling pressure exerted in the formation period is approximately double compared to the holding period). We suggest that this continued institutional selling pressure in the holding period may reflect lack of liquidity in the marketplace. If institutions cannot sell or short-sell the desired volume of losers during the formation period, some of their selling will be postponed, which may delay the prompt convergence of prices to their fundamental values.

The response of institutions to bad news among loser stocks in the formation period can amplify the aforementioned limits to arbitrage. Since institutions are likely the main lenders of shares in the short-sale market, their increased selling activity in the formation period may reduce the amount of shares available for short selling in the holding period, making limits to arbitrage more binding.

In pessimistic periods, small investors are less inclined to buy losers in the formation period and, again, delay their selling until the holding period. The OIBs of large investors are strikingly different. In the formation period they do not exhibit any significant selling pressure for loser stocks and, interestingly, exhibit buying pressure for both winners and losers in the holding period. This suggests that large investors are aware of the general adverse effect of pessimistic sentiment on stock prices and arbitrage the winning stocks to counteract the effects of cognitive dissonance during pessimistic periods.[35]

Overall, the order flow analysis indicates that smaller investors are net buyers of losers in the formation period, and only start to sell these stocks deep into the holding period, prolonging the pricing of bad news. On the contrary, large investors are strong sellers of losing stocks in the formation period, suggesting that they promptly react to negative information. The evidence thus supports the view that smaller investors display stronger evidence of cognitive dissonance and play a key role in contributing to momentum during periods of optimistic sentiment.

We now use the order flow data to provide more direct evidence on the reactions of small and large investors to negative information in the loser portfolio, conditional on sentiment. Specifically, we calculate the average daily OIB for large and small investors following strong negative earnings surprises, where the latter are defined as in Table 10.

The results are given in Table 13. Focusing on small investors, we observe that the selling pressure during the event period is stronger when sentiment is pessimistic than optimistic (–4.1% vs. –1.7%). Although the difference is not statistically significant, the point estimate of the selling pressure is consistent with cognitive dissonance, as small investors react more promptly to negative earnings surprises when they are pessimistic. The adjustment period results show that small investors exert delayed selling pressure, of roughly equal magnitude in optimistic

[35]This result may be reinforced by portfolio rebalancing; specifically, since both winners and losers lose value in pessimistic periods, institutions may become net buyers to restore their appropriate weight in a standard asset allocation setting (e.g., Merton (1971)).

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

and pessimistic periods. However, it is noteworthy that in optimistic periods the adjustment-period selling pressure is 4 times higher (and statistically different) from the selling pressure in the event period, which provides supplemental support to the notion that small investors respond sluggishly to bad news when they are optimistic.

TABLE 13

Post-Event Small and Large Investor OIB for Losers with Low SUE

Table 13 presents daily average OIB for small (Panel A) and large investors (Panel B) in percentages for the periods (−1, 1) and (2, 60), where date 0 is the earnings announcement date (note that the days correspond to trading days). We follow Hvidkjaer's (2006), (2008) methodology to match trades to quotes, and to classify trades into 3 investor categories (small, medium, and large). We calculate the small and large trade imbalances for small and large investors. We subtract from this imbalance the marketwide imbalance for small or large investors on that day to obtain a daily measure of imbalance for small and large investors for each company. In this table we only consider stocks in the loser portfolio with a negative earnings surprise (bottom 30% of SUE). We follow the methodology in Table 11 to calculate earnings surprises. Sentiment is defined as in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. The *t*-statistics are in square brackets and are calculated using clustered standard errors on the company level.

	Horizon			
Sentiment State	(−1, 1)	(2, 60)	Dif.	[*t*-Stat.]
Panel A. OIB for Small Investors				
OPTIMISTIC	−1.70	−7.00	5.30	[5.71]
MILD	−1.80	−3.00	1.20	[1.22]
PESSIMISTIC	−4.10	−6.30	2.20	[1.75]
OPTIMISTIC – PESSIMISTIC	2.40	−0.70		
[*t*-statistic]	[1.40]	[−0.88]		
Panel B. OIB for Large Investors				
OPTIMISTIC	−9.00	−8.00	−1.00	[−0.80]
MILD	−9.00	−4.00	−5.00	[−3.98]
PESSIMISTIC	−2.00	0.00	−2.00	[−0.74]
OPTIMISTIC – PESSIMISTIC	−7.00	−8.00		
[*t*-statistic]	[−3.34]	[−9.59]		

The results for large investors (Panel B of Table 13) tell a completely different story. Large investors sell losers with bad news 4 times more heavily when sentiment is optimistic than pessimistic in the event period (–9% vs. –2%). This finding suggests that large investors are able to time the market and sell more aggressively when sentiment is optimistic. In the adjustment period, when sentiment is optimistic, large investors continue to sell losers at roughly the same rate, whereas in pessimistic periods their average order flow is neutral (–8% vs. 0%).

The results in this section provide additional support to the claim that cognitive dissonance is mainly ingrained in the trades of small investors, who tend to delay the pricing of bad news in the loser portfolio when sentiment is optimistic. Large investors, on the other hand, seem to take into account the general effect of sentiment on the pricing level, and sell losers with bad news more aggressively when sentiment is optimistic.

J. Momentum Profits, Sentiment, and Long-Run Returns

A central prediction of behavioral theories such as Hong and Stein (1999) and Daniel et al. (1998) is that momentum profits revert in the long run. Since

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

we document that momentum profits are *only* significant when investors are optimistic, it is worth examining whether these profits reverse over longer horizons. In this section, we examine the pattern of momentum profits in event time, 5 years after portfolio formation.

Table 14 presents the results. As expected, momentum profits revert only after optimistic periods, regardless of whether returns are risk adjusted. For portfolios constructed in optimistic sentiment states using raw returns, this reversal, as shown in Panel A, is equal to an average monthly return of –0.49%. The corresponding figure in subsequent panels for CAPM- (FF- (1993)) adjusted returns is –0.49% (–0.38%). However, for portfolios formed in pessimistic periods, as expected, there is no reversal. The momentum returns are equal to –0.06% and –0.04% for raw and CAPM-adjusted returns, respectively, and 0.13% for FF-(1993) adjusted returns.

TABLE 14

Long-Run Profits of Momentum Portfolios Conditional on Investor Sentiment

Table 14 presents long-run event time returns for momentum portfolios formed after optimistic and pessimistic periods. For each momentum portfolio we define an event period 13 months after the initial formation period of 6 months. From this event date month onward we compute the average monthly return of this portfolio in the following 5 years. The final return of each portfolio is the geometric average of these monthly average profits. Panel A uses raw returns, Panel B CAPM-adjusted returns, and Panel C returns adjusted according to the FF (1993) 3-factor model. Sentiment is defined as in Table 2. In this table we use 30%–30% cutoff points for optimistic and pessimistic sentiment. To test whether momentum profits in each sentiment state, respectively, are equal to 0, we regress the time series of average monthly momentum profits on OPTIMISTIC, PESSIMISTIC, and MILD sentiment dummy variables, with no intercept. To test if mean profits in OPTIMISTIC sentiment periods are different from profits in PESSIMISTIC sentiment periods, we regress average monthly momentum profits on a MILD sentiment dummy variable and an OPTIMISTIC sentiment dummy variable with a constant. The *t*-statistics of the significance of momentum profits and the difference between profits derived after optimistic and pessimistic periods are calculated using Newey-West (1987) standard errors, where the lag is set to the number of overlapping strategies, which is 6.

		Momentum Portfolio											
Sentiment State		Sell 1	2	3	4	5	6	7	8	9	Buy 10	Buy – Sell	[*t*-Stat.]
Panel A. Raw													
OPTIMISTIC	($n = 121$)	0.81	0.73	0.70	0.68	0.67	0.65	0.62	0.57	0.49	0.32	−0.49	[−5.79]
MILD	($n = 233$)	1.36	1.36	1.37	1.35	1.36	1.34	1.34	1.32	1.30	1.20	−0.17	[−1.86]
PESSIMISTIC	($n = 91$)	1.13	1.28	1.29	1.29	1.30	1.27	1.27	1.24	1.20	1.06	−0.06	[−0.54]
											Opt. – Pes.	−0.43	[−2.90]
Panel B. CAPM													
OPTIMISTIC	($n = 121$)	0.96	0.85	0.80	0.77	0.76	0.73	0.71	0.66	0.60	0.48	−0.49	[−6.26]
MILD	($n = 233$)	0.78	0.83	0.86	0.86	0.87	0.85	0.84	0.82	0.77	0.62	−0.17	[−1.83]
PESSIMISTIC	($n = 91$)	0.37	0.59	0.63	0.65	0.67	0.65	0.65	0.60	0.53	0.33	−0.04	[−0.33]
											Opt. – Pes.	−0.45	[−3.12]
Panel C. FF													
OPTIMISTIC	($n = 121$)	0.60	0.47	0.42	0.41	0.41	0.39	0.38	0.35	0.31	0.21	−0.38	[−4.34]
MILD	($n = 233$)	0.36	0.42	0.48	0.49	0.52	0.51	0.52	0.51	0.48	0.37	0.01	[0.14]
PESSIMISTIC	($n = 91$)	0.10	0.29	0.33	0.36	0.39	0.38	0.40	0.37	0.33	0.22	0.13	[1.13]
											Opt. – Pes.	−0.51	[−3.58]

A noteworthy result in Table 14 is that while mild sentiment portfolios experience marginally significant reversals for raw (–0.17%) or CAPM-adjusted (−0.17%) returns, these profits become insignificant when they are adjusted using the FF (1993) 3-factor model (0.01%). This result suggests that the reversal in the mild sentiment portfolio is related to the HML and/or SMB factor, and thus is not abnormal in the context of the 3-factor model. This finding is in line with FF (1996), who show that the 3-factor model is able to price the long-run reversals

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

documented by DeBondt and Thaler (1985). However, reversals in the optimistic momentum portfolios survive the FF (1993) risk controls.[36]

Another striking feature is that, regardless of the risk adjustment technique, the monotonic pattern in the short-run returns of the optimistic momentum portfolios completely reverts in the long run as in this case, returns decrease as one moves from loser to winner portfolios. A similar, albeit less pronounced pattern is seen in mild sentiment periods. On the contrary, however, the long-run returns of the pessimistic momentum portfolios exhibit no such pattern. Thus, our findings reveal an important link between short-run momentum and long-run reversal, showing that they commonly arise primarily when winner-loser portfolios are formed during periods of positive sentiment.[37]

IV. Concluding Remarks

As price momentum is an important phenomenon in stock returns that is not captured by the FF (1996) 3-factor model, it is worthy of analysis from different perspectives. In this paper, we examine the relationship between price momentum and sentiment. Our hypothesis is that bad news diffuses particularly slowly during periods of optimism, as negative news causes cognitive dissonance in optimistic investors. Our analysis indicates that momentum profits are significant *only* when investors are optimistic (i.e., when the sentiment measure is high). This result is robust to firm size, analyst coverage, market states, risk adjustments, and alternative specifications for investor sentiment.

We calculate net order flows using transactions data and show that smaller (and presumably less sophisticated) investors are reluctant to sell losing stocks in optimistic periods. On the contrary, large investors are more prompt sellers of losers in optimistic periods. This result is in line with the notion that small investors are afflicted with cognitive dissonance when confronted with losing stocks in periods of positive sentiment. In addition, we show that long-run price reversals occur *only* after optimistic periods. This is consistent with the idea that the actions of "momentum traders" exacerbate price continuations during optimistic periods, and subsequently, prices correct toward fundamentals, as argued by Hong and Stein (1999).

The recent findings of Chui, Titman, and Wei (2010) show that momentum is more pronounced in individualistic cultures. This raises the question of whether the asymmetric momentum pattern we have documented for the United States, where individualistic attitudes are considered to be higher than in other cultures,

[36] We also perform a regression similar to Panel C of Table 4, where the dependent variable is the long-term momentum portfolio (as described in Table 14). In the regression, the stock market variables are not significant, whereas the coefficient on our sentiment variable is negative and strongly significant. This further supports the notion that momentum profits after high sentiment periods reverse more strongly in the long run.

[37] Cooper et al. (2004) and Lee and Swaminathan (2000) also show that the link between short-term momentum and long-term reversals depends on market returns and turnover, respectively. Our study complements these papers by showing that an exogenous measure of optimism, namely, sentiment, predicts a significant difference in the long-run performance of momentum portfolios.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

gains support in countries characterized by less individualism. Exploration of this issue would seem to be an interesting area for future research.

References

Acemoglu, D., and A. Scott. "Consumer Confidence and Rational Expectations: Are Agents' Beliefs Consistent with the Theory?" *Economic Journal*, 104 (1994), 1–19.

Arkes, H.; L. Herren; and A. Isen. "The Role of Potential Loss in the Influence of Affect on Risk-Taking Behavior." *Organizational Behavior and Human Decision Processes*, 42 (1988), 181–193.

Asness, C.; T. Moskowitz; and L. Pedersen. "Value and Momentum Everywhere." Working Paper, New York University (2009).

Baker, M., and J. Wurgler. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance*, 61 (2006), 1645–1680.

Baker, M., and J. Wurgler. "Investor Sentiment in the Stock Market." *Journal of Economic Perspectives,* 21 (2007), 129–151.

Bergman, N., and S. Roychowdhury. "Investor Sentiment and Corporate Disclosure." *Journal of Accounting Research*, 46 (2008), 1057–1083.

Bower, G. "Mood and Memory." *American Psychologist*, 36 (1981), 129–148.

Bower, G. "Mood Congruity of Social Judgment." In *Emotion and Social Judgments*, J. Forgas, ed. Oxford, England: Pergamon Press (1991).

Bracha, A., and D. Brown. "Affective Decision Making: A Theory of Optimism Bias." *Games and Economic Behavior,* 75 (2012), 67–80.

Brown, G. W., and M. T. Cliff. "Investor Sentiment and Asset Valuation." *Journal of Business,* 78 (2005), 405–440.

Brunnermeier, M., and J. Parker. "Optimal Expectations." *American Economic Review*, 95 (2005), 1092–1118.

Chan, L. K. C.; N. Jegadeesh; and J. Lakonishok. "Momentum Strategies." *Journal of Finance,* 51 (1996), 1681–1713.

Charoenrook, A. "Does Sentiment Matter?" Working Paper, Vanderbilt University (2003).

Chordia, T., and L. Shivakumar. "Momentum, Business Cycle, and Time-Varying Expected Returns." *Journal of Finance,* 57 (2002), 985–1019.

Chui, A. C. W.; S. Titman; and K. C. J. Wei. "Individualism and Momentum Around the World." *Journal of Finance*, 65 (2010), 361–392.

Conrad, J., and G. Kaul. "An Anatomy of Trading Strategies." *Review of Financial Studies*, 11 (1998), 489–519.

Cooper, M. J.; R. C. Gutierrez, Jr.; and A. Hameed. "Market States and Momentum." *Journal of Finance*, 59 (2004), 1345–1365.

Cornelli, F.; D. Goldreich; and A. Ljungqvist. "Investor Sentiment and Pre-IPO Markets." *Journal of Finance*, 61 (2006), 1187–1216.

Daniel, K.; D. Hirshleifer; and A. Subrahmanyam. "Investor Psychology and Security Market Under- and Overreactions." *Journal of Finance*, 53 (1998), 1839–1885.

D'Avolio, G. "The Market for Borrowing Stock." *Journal of Financial Economics*, 66 (2002), 271–306.

DeBondt, W., and R. Thaler. "Does the Stock Market Overreact?" *Journal of Finance,* 40 (1985), 793–805.

Doukas, J., and P. McKnight. "European Momentum Strategies, Information Diffusion, and Investor Conservatism." *European Financial Management*, 11 (2005), 313–338.

Edmans, A.; D. Garcia; and Ø. Norli. "Sports Sentiment and Stock Returns." *Journal of Finance*, 62 (2007), 1967–1998.

Fama, E., and K. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E., and K. French. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance*, 51 (1996), 55–84.

Festinger, L. *A Theory of Cognitive Dissonance.* Stanford, CA: Stanford University Press (1957).

Fisher, K. L., and M. Statman. "Consumer Confidence and Stock Returns." *Journal of Portfolio Management*, 30 (2003), 115–127.

Frazzini, A., and O. Lamont. "Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns." *Journal of Financial Economics,* 88 (2008), 299–322.

Grinblatt, M., and B. Han. "Prospect Theory, Mental Accounting, and Momentum." *Journal of Financial Economics,* 78 (2005), 311–339.

Grinblatt, M., and M. Keloharju. "Sensation Seeking, Overconfidence, and Trading Activity." *Journal of Finance,* 64 (2009), 549–578.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press

Grundy, B., and J. S. Martin. "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing." *Review of Financial Studies,* 14 (2001), 29–78.
Hirshleifer, D., and T. Shumway. "Good Day Sunshine: Stock Returns and the Weather." *Journal of Finance*, 58 (2003), 1009–1032.
Hong, H.; T. Lim; and J. Stein. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance,* 55 (2000), 265–295.
Hong, H., and J. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance*, 54 (1999), 2143–2184.
Hvidkjaer, S. "A Trade-Based Analysis of Momentum." *Review of Financial Studies*, 19 (2006), 457–491.
Hvidkjaer, S. "Small Trades and the Cross-Section of Stock Returns." *Review of Financial Studies,* 21 (2008), 1123–1151.
Jegadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, 48 (1993), 65–91.
Jegadeesh, N., and S. Titman. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance*, 56 (2001), 699–720.
Johnson, E., and A. Tversky. "Affect, Generalization, and the Perception of Risk." *Journal of Personality and Social Psychology*, 45 (1983), 20–31.
Johnson, T. "Rational Momentum Effects." *Journal of Finance,* 57 (2002), 585–608.
Kaplanski, G., and H. Levy. "Sentiment and Stock Prices: The Case of Aviation Disasters." *Journal of Financial Economics*, 95 (2010), 174–201.
Lakonishok, J.; I. Lee; N. Pearson; and A. Poteshman. "Option Market Activity." *Review of Financial Studies*, 20 (2007), 813–857.
Lakonishok, J.; A. Shleifer; and R. Vishny. "Contrarian Investment, Extrapolation, and Risk." *Journal of Finance,* 49 (1994), 1541–1578.
Lee, C. M. C.; A. Shleifer; and R. H. Thaler. "Investor Sentiment and the Closed-End Fund Puzzle." *Journal of Finance*, 46 (1991), 75–109.
Lee, C. M. C., and B. Swaminathan. "Price Momentum and Trading Volume." *Journal of Finance,* 55 (2000), 2017–2069.
Lemmon, M., and E. Portniaguina. "Consumer Confidence and Asset Prices: Some Empirical Evidence." *Review of Financial Studies*, 19 (2006), 1499–1529.
Lewellen, J. "Momentum and Autocorrelation in Stock Returns." *Review of Financial Studies,* 15 (2002), 533–563.
Livnat, J., and C. Petrovits. "Investor Sentiment, Post-Earnings Announcement Drift, and Accruals." Working Paper, New York University (2008).
Ludvigson, S. "Consumer Confidence and Consumer Spending." *Journal of Economic Perspectives*, 18 (2004), 29–50.
Malmendier, U., and D. Shanthikumar. "Are Small Investors Naive About Incentives?" *Journal of Financial Economics*, 85 (2007), 457–489.
McLean, R. D., and M. Zhao. "Investor Sentiment and Real Investment." Working Paper, University of Alberta (2009).
Merton, R. C. "Optimal Consumption and Portfolio Rules in a Continuous-Time Model." *Journal of Economic Theory*, 3 (1971), 373–413.
Moskowitz, T., and M. Grinblatt. "Do Industries Explain Momentum?" *Journal of Finance*, 54 (1999), 1249–1290.
Nagel, S. "Short Sales, Institutional Investors and the Cross-Section of Stock Returns." *Journal of Financial Economics,* 78 (2005), 277–309.
Newey, W., and K. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*, 55 (1987), 703–708.
Odean, T. "Do Investors Trade Too Much?" *American Economic Review*, 89 (1999), 1279–1298.
Puri, M., and D. Robinson. "Optimism and Economic Choice." *Journal of Financial Economics*, 86 (2007), 71–99.
Qiu, L., and I. Welch. "Investor Sentiment Measures." NBER Working Paper No. 10794 (2006).
Rouwenhorst, K. G. "International Momentum Strategies." *Journal of Finance*, 53 (1998), 267–284.
Slovic, P. *The Perception of Risk.* London, UK: Earthscan Publications (2000).
Veldkamp, L. "Slow Boom, Sudden Crash." *Journal of Economic Theory*, 124 (2005), 230–257.
Veronesi, P. "Stock Market Overreaction to Bad News in Good Times: A Rational Expectations Equilibrium Model." *Review of Financial Studies*, 12 (1999), 975–1007.
Whaley, R. "Understanding the VIX." *Journal of Portfolio Management*, 35 (2009), 98–105.
Wright, W. F., and G. H. Bower. "Mood Effects on Subjective Probability Assessment." *Organizational Behavior and Human Decision Processes*, 52 (1992), 276–291.

https://doi.org/10.1017/S0022109012000592 Published online by Cambridge University Press