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Investor Sentiment, Trading Behavior and Informational Efficiency in Index Futures Markets

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Abstract

This paper shows that traders in index futures markets are positive feedback traders—they buy when prices increase and sell when prices decline. Positive feedback trading appears to be more active in periods of high investor sentiment. This finding is consistent with the notion that feedback trading is driven by expectations of noise traders. Consistent with the noise trading hypothesis, order flow in index futures markets is less informative when investors are optimistic. Transitory volatility measured at high frequencies also appears to decline in periods of bullish sentiment, suggesting that sentiment-driven trading increases market liquidity.

Keywords: feedback trading, investor sentiment, informational efficiency, market microstructure, futures markets

JEL Classifications: G10, G14

1. Introduction

"Follow the trend. The trend is your friend." is an old saying on Wall Street. In its simplest form, trend chasing involves buying securities after price increases and

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selling after price declines. Such trading strategies are called positive feedback trading. As in the case of the Nasdaq stock bubble of the late 1990s, positive feedback traders can push prices away from fundamental values. Furthermore, De Long, Shleifer, Summers, and Waldmann (1990) show theoretically that rational speculators do not fully eliminate, and can even amplify, the effect of positive feedback trading on asset prices. Consistent with this notion, Shu (2007) finds that positive feedback trading by institutional investors intensifies momentum in stock returns and reduces price efficiency.

Experimental and survey evidence discussed by De Long, Shleifer, Summers, and Waldmann (1990) supports the notion that investors often follow positive feedback trading strategies. There is also empirical evidence from a variety of markets that at least some investors are positive feedback traders. Sentana and Wadhwani (1992) use a hundred years of daily stock return data to show that the relation between volatility and return autocorrelations is consistent with positive feedback trading. Bange (2000), Sias (2007), and Nofsinger and Sias (1999) show that changes in portfolio holdings of individual and institutional investors observed at monthly, quarterly and annual intervals are driven, at least in part, by positive feedback trading.

Few studies examine feedback trading in a microstructure setting. Cohen and Shin (2003) find evidence of positive feedback trading using tick-by-tick data for the U.S. Treasury market. This trading activity appears to increase on more volatile days. Finally, Danielsson and Love (2006) show positive feedback trading in the spot foreign exchange market by analyzing intraday returns and order flows.

In a study directly related to this paper, Antoniou, Koutmos, and Pericli (2005) analyze positive feedback trading in spot index and index futures markets of six developed nations using an indirect approach based on daily returns, similar to the approach used by Sentana and Wadhwani (1992). They find no evidence of positive feedback trading in index futures, concluding that rational speculators trading index futures may help stabilize the underlying stock prices. Trading in government bond and foreign exchange markets studied by Cohen and Shin (2003) and Danielsson and Love (2006) is dominated by large dealers, who hold considerable inventory. Index futures markets have a very different microstructure. In particular, Manaster and Mann (1996) show that market makers, or "scalpers," in futures markets tend to hold relatively small open positions and quickly reduce their inventory exposure. Such microstructure characteristics of futures markets may affect the propensity of futures traders to engage in positive feedback trading.

This paper uses high frequency price and order flow data from two actively traded index futures markets to directly examine whether futures traders use feedback trading strategies. In contrast to Antoniou, Koutmos, and Pericli (2005), the results show that index futures traders are positive feedback traders, i.e., they initiate buy trades after price increases and sell trades after price declines. Such positive feedback trading becomes more prevalent in index futures markets over our sample period.

In further analysis, we examine whether positive feedback trading is related to investor sentiment. We find that the intensity of positive feedback trading increases in periods of bullish sentiment and declines in periods of bearish sentiment. This result is consistent with the notion that positive feedback trading is driven, at least in part, by expectations of uninformed investors. Our approach also allows analyzing time variation in the informativeness of order flow. Consistent with the noise trading hypothesis, we find that the informational content of order flow tends to be lower when investors are optimistic.

Finally, the paper examines the relation between investor sentiment and transitory volatility, with the investor sentiment used as a proxy for the amount of noise trading activity. The results show that transitory volatility, estimated using trade-by-trade data, declines in periods of bullish sentiment. This finding is consistent with uninformed trading increasing market liquidity, helping to reduce transitory price fluctuations at short horizons. This result also indicates that the increased positive feedback trading activity in periods of bullish sentiment does not make index futures prices noisier.

2. Hypotheses

The first contribution of this paper is to directly examine whether index futures traders use positive feedback strategies. Given that Antoniou, Koutmos, and Pericli (2005) find no evidence of feedback trading in index futures markets, we test the following hypothesis (stated in the null form):

Hypothesis 1. Order flow initiated by index futures traders tends to be unrelated to previous price changes.

Positive feedback trading is commonly identified with (possibly irrational) noise traders.[1] Baker and Wurgler (2006) show evidence consistent with demand for stocks by uninformed investors being driven by investor sentiment. For example, when investors are bullish, they buy stocks, driving stock prices up and subsequent returns down. Noise traders tend to trade more when they are bullish than when they are bearish (e.g., Baker and Stein, 2004).[2] Therefore, given that noise traders are prone to trend chasing, one can expect positive feedback trading to be more prevalent when investors are optimistic. This leads to the following hypothesis:

Hypothesis 2. There is a positive relation between the intensity of positive feedback trading and investor sentiment.

Asset prices contain information. Some information comes from public news releases and can be incorporated into prices without trading. However, French and Roll (1986) show that private information, which is produced by informed investors and impounded into prices through trading, plays a more important role. The notion that investor order flow carries information to the market is well established in the

[1] Rational reasons for positive feedback trading include portfolio insurance strategies and the activation of stop-loss orders.

[2] Yan and Ferris (2004) show that trading activity of online investors increases when investors are bullish. Baker and Wurgler (2006) use equity market turnover as one of the components of their sentiment index.

theoretical and empirical market microstructure literature. (See, for example, Kyle, 1985; Glosten and Milgrom, 1985; Hasbrouck, 1991.)

Private information in the common sense is unlikely to play an important role in index futures markets, because such information becomes "diversified" in broad market indexes (e.g., Subrahmanyam, 1991). However, market participants use different models and different analytical resources to translate information about economic fundamentals into subjective valuations (e.g., Kandel and Pearson, 1995). Investor order flow aggregates such varied interpretations of information signals. Consistent with this notion, Evans and Lyons (2002) show that order flow in the spot foreign exchange market contains information that determines foreign exchange rates. Similarly, Brandt and Kavajecz (2004) find that investor order flow in the U.S. Treasury market affects the yield curve.

We also expect order flow to be important to price discovery in index futures markets. As noise trading increases in high-sentiment states, such order flow is likely to become less informative. The corresponding testable implication is that:

Hypothesis 3. There is a negative relation between the informativeness of order flow and investor sentiment.

Sentiment-driven uninformed trading could introduce noise into the prices by pushing the prices away from fundamental values. Consistent with this notion, Brown and Cliff (2005) find that stock market valuation errors are positively correlated with investor sentiment. On the other hand, Baker and Stein (2004) show theoretically that trading activity by noise traders increases the market liquidity. Higher market liquidity can help to stabilize temporary price fluctuations and facilitate price discovery. The effect of sentiment-driven noise trading on transitory volatility is ultimately an empirical question. Assuming that investor sentiment can be used as a proxy for noise trading activity, we test the following hypothesis stated in null form:

Hypothesis 4. Transitory volatility is unrelated to investor sentiment.

3. Data

We consider the S&P 500 and Nasdaq-100 E-mini index futures markets. The E-mini futures trade on GLOBEX electronic trading system operated by the Chicago Mercantile Exchange (CME). These contracts are sized at one-fifth of the index futures contracts traded on the CME floor. Trading in the E-mini futures is extremely active. Furthermore, Hasbrouck (2003) shows that the E-mini futures dominate price discovery in the S&P 500 and Nasdaq-100 index markets.

We use transactions data for the two E-mini futures contracts for the regular trading hours from 9:30 a.m. to 4:15 p.m. ET. The data come from the Commodity Futures Trading Commission (CFTC) and contain separate records for buy and sell side of each trade. The available data fields include the trade date, order submission time and trade time to the nearest second, the contract month, buy/sell code, number of contracts traded, trade price, customer type indicator (CTI), and a unique match code that allows identifying both sides of the same trade. We examine trades for 2002–2004 and consider only the most actively traded contract in each market for every trading day. Shortened pre-holiday days are removed from the sample. The sample period includes part of the post-dot-com bubble bear market and the market recovery in the spring of 2003.

To obtain the order flow of index futures traders, we need to classify the E-mini trades as buyer- or seller-initiated. Our data include order submission times for both sides of each trade. In a limit order market like GLOBEX, aggressive orders are executed immediately, whereas limit orders tend to spend time in the order book waiting for execution. Therefore, we classify trades as buyer- or seller-initiated by assuming that the order with the later submission time initiated the trade. We also use the tick rule to sign trades with the same submission times for both sides. Finucane (2000) shows that, when zero-tick trades are removed, the tick rule performs well as a trade classification algorithm. Therefore, we remove zero-tick trades with the same submission times for both sides of the trade.[3]

Once the trades are classified as buyer- or seller-initiated, we calculate the net order flow for each one-minute interval as the number of buyer-initiated contracts bought less the number of seller-initiated contracts sold. Summary statistics for our sample period are shown in Table 1. The average number of trades per minute is about 261 for the E-mini S&P 500 market and about 149 for the E-mini Nasdaq-100 market. The median trade size of only two contacts in both markets is consistent with small retail traders accounting for a significant share of the trading. The order flows show some persistence, with first-order autocorrelation of about 0.20 in E-mini S&P 500 market and about 0.13 in the E-mini Nasdaq-100 market. The one-minute returns exhibit a small negative autocorrelation.

4. Methods and results

4.1. Estimation of the VAR

We use a vector autoregression (VAR) of returns and order flows, which is a modification of the VAR model introduced by Hasbrouck (1991). Our model accounts for contemporaneous feedback trading, i.e., the effect of contemporaneous returns on order flow. The VAR takes the following form:

$$\begin{aligned} R_t &= a_1 + \sum_{i=0}^{n} b_{1i} F_{t-i} + \sum_{i=1}^{m} c_{1i} R_{t-i} + \varepsilon_{1t} \\ F_t &= a_2 + \sum_{i=1}^{n} b_{2i} F_{t-i} + \sum_{i=0}^{m} c_{2i} R_{t-i} + \varepsilon_{2t}, \end{aligned} \tag{1}$$

[3] These trades account for less than 9% of the total number of trades.

Table 1

Summary statistics

The statistics for the number of trades, returns and order flows are computed for one-minute intervals. Returns are calculated as 100 times the log difference of the price. Only the prices of buyer-initiated trades are used in the return calculation to reduce the effects of the bid-ask bounce. The sample period is from January 1, 2002 through December 30, 2004.

	Mean	Median	Standard deviation	Autocorrelation (lags) 1	3	5
E-mini S&P 500						
Trade size (contracts)	5.25	2	11.05	–	–	–
Number of trades	261.0	209	202.3	0.6239**	0.5006**	0.4176**
Returns	0.000044	0	0.0523	−0.0160**	−0.0089**	−0.0109**
Order flows	−6.77	−5	697.55	0.2013**	0.0373**	0.0122**
E-mini Nasdaq-100						
Trade size (contracts)	4.20	2	7.16	–	–	–
Number of trades	148.7	122	112.1	0.6474**	0.5023**	0.4555**
Returns	−0.000042	0	0.0827	−0.0259**	−0.0043*	−0.0098**
Order flows	−3.87	−1	293.06	0.1296**	0.0221**	−0.0004

**, * indicate statistical significance at the 0.01 and 0.05 level, respectively.

where F_t is the net order flow in period t and R_t is the return in period t. Both returns and order flows are calculated in one-minute intervals. Since the bid-ask quotes for the E-mini contracts are not reported in the data, the one-minute continuously compounded returns are calculated using trade prices. Only the prices of buyer-initiated trades are used in the return calculation to reduce the effects of the bid-ask bounce. Three lags of order flows and two lags of returns are selected using the Schwartz Information Criterion. The coefficients of the order flow terms in the return equation reflect the price impact of order flow, whereas the coefficients of contemporaneous and lagged return in the order flow equations measure the feedback from price changes to trading activity.

We use time aggregation of returns and order flow primarily because it alleviates the simultaneity problem between the trade prices and trade sizes discussed by Hasbrouck (1991). Furthermore, given the intensity of the trading activity in the E-mini markets (several trades per second on average), using transaction time as in Hasbrouck (1991) would dramatically shorten the time horizon captured by the VAR model.

The key difference of our model from the one introduced by Hasbrouck (1991) is the contemporaneous return term in the order flow equation. With time aggregation, it becomes impossible to argue that causality runs only from trades to price changes and not in the opposite direction. It is plausible that trading decisions even at short horizons are influenced by the immediately preceding price changes, which are classified as contemporaneous when time aggregation is used. Danielsson and Love (2006) suggest including contemporaneous return in the order flow equation to account for such contemporaneous feedback trading. The high trading frequency in the E-mini markets and the use of computer-generated orders by some traders make it essential to account for contemporaneous feedback trading.

With the contemporaneous return included in the model, the VAR can no longer be identified recursively. However, Danielsson and Love (2006) suggest that returns and order flows from related markets can be used as instruments to identify the VAR's structural parameters. To estimate a VAR for the spot USD/EUR market, they use instruments obtained from the USD/GBP and GPB/EUR markets. They show that adding the contemporaneous feedback in the VAR model significantly affects the estimates of the informativeness of order flow and the amount of feedback trading.

The S&P 500 and Nasdaq-100 E-mini futures markets are closely related and traded on the same electronic platform. The correlation of contemporaneous one-minute returns in the two markets is about 0.76, making them good instruments for each other. The order flows in the two E-mini markets are also highly correlated. Specifically, the correlation between one-minute order flows in the two E-mini markets is about 0.64. Therefore, we use contemporaneous order flow and return in the E-mini Nasdaq-100 futures as instruments for the E-mini S&P 500 order flow and return, and vice versa.[4]

Following Danielsson and Love (2006), the VAR model is estimated using two-stage least squares. Panel A in Table 2 reports the VAR estimates for the full sample, with the contemporaneous returns included in the order flow equation. For the E-mini S&P 500 futures, the coefficient of the contemporaneous order flow in the return equation is about 0.08, suggesting that a 1,000-contract buy imbalance pushes the price up by about eight basis points. More interestingly, the coefficients of the contemporaneous and lagged returns in the order flow equation are positive and strongly significant, indicating positive feedback trading. For the E-mini S&P 500 futures, a ten-basis-point positive return leads to an immediate positive net order flow of about 1,000 contracts. The results are qualitatively similar in the E-mini Nasdaq-100 market.

As a robustness check, we reestimate the VAR with OLS after omitting the contemporaneous return from the order flow equation. The results are in Panel B of Table 2. Consistent with Danielsson and Love (2006), the coefficient of the order flow in the return equation declines significantly for both markets. The R^2 of the order flow equation declines to about 5% for the E-mini S&P 500 market and about 2% for the E-mini Nasdaq-100 market. The coefficients of lagged returns in the order flow equation are positive and significant, showing evidence of positive feedback trading.

To examine the information content of order flow and the intensity of feedback trading activity, we calculate cumulative impulse response functions by forecasting the VAR after a shock to one of the variables. Figure 1 reports the impulse responses for the VAR with and without contemporaneous feedback. The figure shows that a return shock leads to a significant amount of positive feedback trading. Specifically, based on the VAR with contemporaneous feedback, a ten-basis-point return shock

[4] When we use lagged, rather than contemporaneous, returns and order flows from the other E-mini market as instruments in the VAR, the results are qualitatively similar, although the coefficient standard errors increase.

Table 2

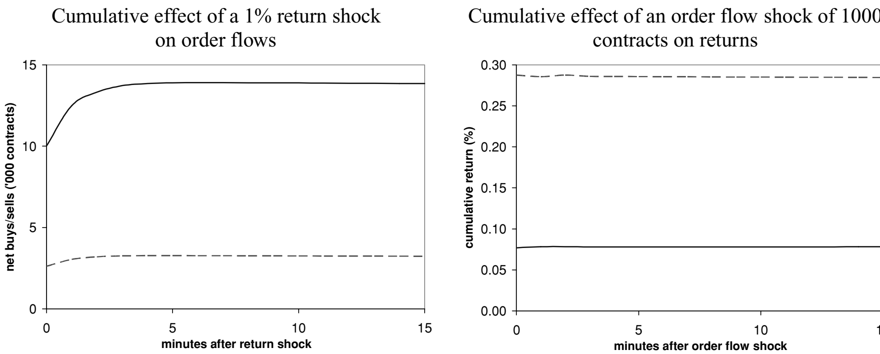
VAR results

Returns are calculated as 100 times the log difference of the price. Order flows are in thousands of contracts. Returns and order flows are aggregated in one-minute intervals. Absolute values of t-statistics calculated using heteroskedasticity-consistent standard errors are in parentheses. The sample period is from January 1, 2002 through December 30, 2004.

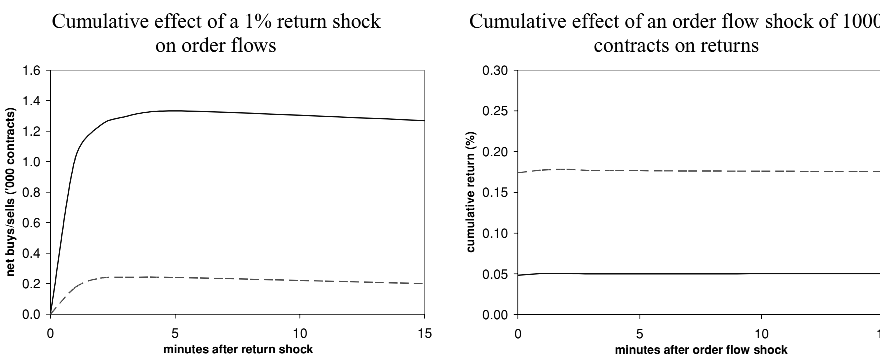
	E-mini S&P 500		E-mini Nasdaq-100	
	R_t equation	F_t equation	R_t equation	F_t equation
Panel A: VAR with contemporaneous feedback trading				
Constant	0.00048 (5.97)	−0.0062 (6.34)	0.00093 (7.00)	−0.0033 (7.81)
Flow_t	0.0765 (232.09)		0.2866 (224.09)	
Return_t		10.03 (235.44)		2.62 (226.89)
Return_{t-1}	−0.1082 (28.22)	1.32 (33.39)	−0.0991 (30.83)	0.30 (34.00)
Return_{t-2}	−0.0123 (3.49)	0.14 (4.06)	−0.0106 (3.65)	0.04 (5.17)
Flow_{t-1}	−0.0076 (30.54)	0.1097 (35.31)	−0.0152 (18.49)	0.0633 (22.40)
Flow_{t-2}	−0.0031 (13.95)	0.0397 (14.02)	−0.0087 (11.33)	0.0293 (11.01)
Flow_{t-3}	−0.0022 (15.14)	0.0269 (13.72)	−0.0059 (10.52)	0.0191 (9.52)
Adjusted R^2	0.26	0.42	0.22	0.37
DW statistic	2.00	2.00	2.00	2.00
Panel B: VAR without contemporaneous feedback trading				
Constant	0.00032 (4.44)	−0.0056 (4.52)	0.00054 (4.55)	−0.0035 (6.69)
Flow_t	0.0481 (266.05)		0.1735 (254.21)	
Return_{t-1}	−0.0780 (20.11)	1.03 (31.73)	−0.0779 (24.00)	0.18 (21.97)
Return_{t-2}	−0.0102 (2.84)	0.10 (3.28)	−0.0038 (1.27)	0.06 (7.01)
Flow_{t-1}	−0.0035 (18.13)	0.1441 (39.48)	−0.0047 (7.80)	0.0935 (27.28)
Flow_{t-2}	−0.0020 (11.76)	0.0359 (10.62)	−0.0057 (10.27)	0.0259 (7.91)
Flow_{t-3}	−0.0017 (16.14)	0.0203 (7.96)	−0.0043 (10.91)	0.0145 (5.67)
Adjusted R^2	0.41	0.05	0.38	0.02
DW statistic	2.00	2.00	2.00	2.00

results in a positive net order flow of about 1,400 contracts in the E-mini S&P 500 market and about 300 contracts in the E-mini Nasdaq-100 market. This result appears to reject Hypothesis 1. It also contrasts with the indirect evidence of Antoniou, Koutmos, and Pericli (2005), who conclude that index futures traders are not positive feedback traders. Positive feedback trading appears to be active in the E-mini index futures markets, although it may not drive the dynamics of daily returns. Figure 1 also shows the cumulative impact of order flows on returns. A larger long-run price impact implies a higher information content of trades.

The impulse responses for the VAR without contemporaneous feedback are shown in Panel B of Figure 1. The information content of trades and positive feedback trading appear to be smaller compared to VAR with contemporaneous feedback. In the results that follow, we use the VAR with contemporaneous feedback because, as Danielsson and Love (2006) argue, this model specification provides more accurate estimates of the price impact of order flow and of feedback trading.



Panel A. VAR with contemporaneous feedback



Panel B. VAR without contemporaneous feedback

Figure 1

Cumulative impulse response functions

The solid lines give the impulse responses for the E-mini S&P 500 futures and the dashed lines give the impulse responses for the E-mini Nasdaq-100 futures. The sample period is from January 1, 2002 through December 30, 2004.

4.2. Effect of investor sentiment on feedback trading and informativeness of order flow

The VAR results in Table 1 and Figure 1 show the average effect of order flow on prices and the average feedback effect of returns on trading. Hypotheses 2 and 3 address whether these effects are related to investor sentiment. To test these hypotheses, we need a proxy for investor sentiment. We use two direct measures of investor sentiment that appear in the literature (e.g., Brown and Cliff, 2004). The first measure is obtained from Investor Intelligence and represents the outlook of about 150 independent market newsletters. Investor Intelligence classifies newsletters as

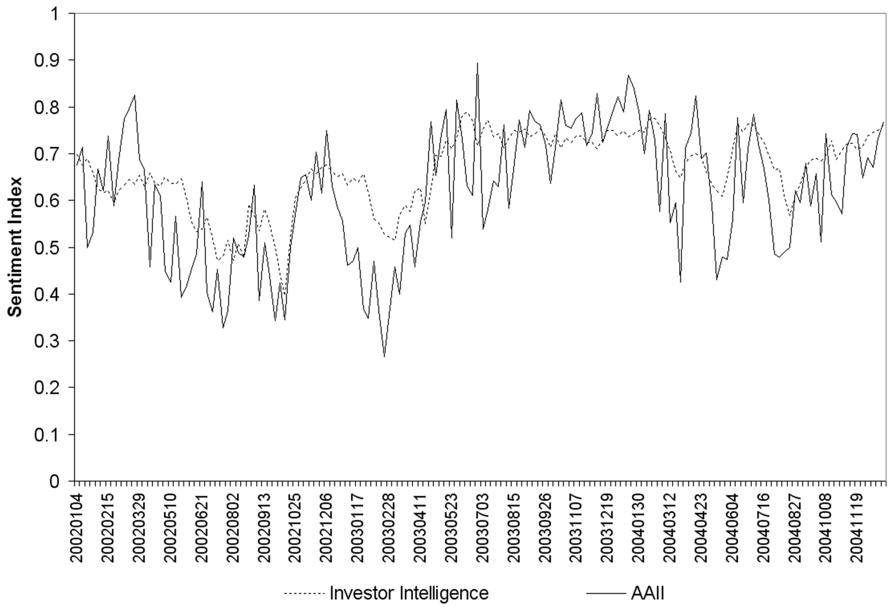


Figure 2

Time variation in investor sentiment

bullish, bearish or correction and releases the resulting percentages every Friday. The second measure is from a weekly (every Thursday) survey of individual investors conducted by the American Association of Individual Investors (AAII). The responses are classified as bullish, bearish or neutral.

Following Fisher and Statman (2006), for each of the two sentiment surveys we compute an investor sentiment index as a ratio of the percentage of bullish investors to the sum of the percentages of bullish and bearish investors.[5] Figure 2 plots the two sentiment indexes during our sample period.[6] Unsurprisingly, they tend to move together. The correlation between the two measures is about 0.71, indicating that the two measures are closely related but not identical. The AAII sentiment index tends to be more volatile than the Investor Intelligence index.

To test Hypotheses 2 and 3, we estimate the following VAR, similar to Cohen and Shin (2003):

[5] The results using the spread between the percentages of bullish and bearish investors are similar.

[6] We also examine the distribution of the investor sentiment measures over a longer period, from July 1987 to December 2005. The standard deviations of the two sentiment indexes over this sample period are similar to the standard deviations over 2002–2004, whereas the average investor sentiment is somewhat higher in 2002–2004.

$$
\begin{aligned}
R_t &= a_1 + \sum_{i=0}^{3} \left(b_{1i} + b_{1i}^L D_{t-i}^L + b_{1i}^H D_{t-i}^H\right) F_{t-i} \\
&\quad + \sum_{i=1}^{2} \left(c_{1i} + c_{1i}^L D_{t-i}^L + c_{1i}^H D_{t-i}^H\right) R_{t-i} + \varepsilon_{1t} \\
F_t &= a_2 + \sum_{i=1}^{3} \left(b_{2i} + b_{2i}^L D_{t-i}^L + b_{2i}^H D_{t-i}^H\right) F_{t-i} \\
&\quad + \sum_{i=0}^{2} \left(c_{2i} + c_{2i}^L D_{t-i}^L + c_{2i}^H D_{t-i}^H\right) R_{t-i} + \varepsilon_{2t}.
\end{aligned} \tag{2}
$$

The dummy variable D_t^L is equal to one on days when the investor sentiment measure is below its 25th percentile. Similarly, the dummy variable D_t^H is equal to one on days when the investor sentiment measure is above its 75th percentile. This specification allows a joint estimation of the VAR in three subsamples: normal days, low-sentiment days and high-sentiment days.

The subsample results are in Table 3. In both E-mini markets and for both sentiment measures, the effect of recent returns on order flow tends to be significantly greater in periods of bullish sentiment. Supporting Hypothesis 2, this result shows that positive feedback trading increases when investors are optimistic. This finding suggests that sentiment-driven noise trading is likely to increase positive feedback trading. The long-run price impact of order flow is significantly smaller on high-sentiment days than on low-sentiment days. Consistent with Hypothesis 3, this result implies a negative relation between information content of order flow and investor sentiment.

Our VAR captures serial dependencies in returns and order flows at very short horizons. Therefore, it is possible that the price impacts that we interpret as permanent are, at least in part, temporary price pressure effects that are eventually reversed. Under this interpretation, the results suggest that index futures markets tend to be more liquid in periods of bullish sentiment, with the higher liquidity reducing the price pressure effects. The subsample results also show that, controlling for feedback trading, the persistence of order flow is significantly lower in high-sentiment periods. At the same time, the negative serial correlation of one-minute returns increases in periods of bullish sentiment.

An alternative way to test Hypotheses 2 and 3 is to estimate the VAR separately for each week and examine time variation in the impulse responses. We use weekly estimation intervals because our investor sentiment measures are available at weekly intervals. Figure 3 shows the intensity of feedback trading for each week in the sample for both E-mini futures markets. There seems to be an increase in positive feedback trading in 2003 and 2004 and substantial variation throughout the sample.

We use the following regression model to test Hypothesis 2:

$$CF_t = \alpha + \beta_1 Sentiment_t + \beta_2 t + \beta_3 t^2 + \beta_4 Volume_t + \varepsilon_t. \tag{3}$$

Table 3

VAR results in subsamples

The table reports sums of different combinations of coefficients from the following VAR:

$$R_t = a_1 + \sum_{i=0}^{3}\left(b_{1i} + b_{1i}^{L} D_{t-i}^{L} + b_{1i}^{H} D_{t-i}^{H}\right) F_{t-i} + \sum_{i=1}^{2}\left(c_{1i} + c_{1i}^{L} D_{t-i}^{L} + c_{1i}^{H} D_{t-i}^{H}\right) R_{t-i} + \varepsilon_{1t},$$

$$F_t = a_2 + \sum_{i=1}^{3}\left(b_{2i} + b_{2i}^{L} D_{t-i}^{L} + b_{2i}^{H} D_{t-i}^{H}\right) F_{t-i} + \sum_{i=0}^{2}\left(c_{2i} + c_{2i}^{L} D_{t-i}^{L} + c_{2i}^{H} D_{t-i}^{H}\right) R_{t-i} + \varepsilon_{2t},$$

where D_t^L is a dummy variable equal to one on days when the given investor sentiment measure is below the 25th percentile and D_t^L equals one the given investor sentiment measure is above the 75th percentile for our sample. The reported values are sums of coefficients for the different subsamples. For example, the values in the row "Normal" days for the order flow coefficients in the return equation are calculated as $\sum_{i=0}^{3} b_{1i}$. The values in the "Low Sentiment" row for the order flow coefficients in the return equation are calculated as $\sum_{i=0}^{3}(b_{1i} + D_{t-i}^{L})$, and so on. The values in the "Low vs. Normal" row show additional effects in the low-sentiment subsample and are calculated as $\sum_{i=0}^{3}(D_{t-i}^{L})$, and so on. Returns are calculated as 100 times the log difference of the price. Order flows are in thousands of contracts. Returns and order flows are aggregated in one-minute intervals. The coefficients of primary interest are shown in bold. The sample period is from January 1, 2002 through December 30, 2004.

	Investor Intelligence sentiment index				AAII sentiment index			
	E-mini S&P 500		E-mini Nasdaq-100		E-mini S&P 500		E-mini Nasdaq-100	
	R_t equation	F_t equation	R_t equation	F_t equation	R_t equation	F_t equation	R_t equation	F_t equation
Coefficients on order flow								
"Normal" days	0.0555**	0.1679**	0.2335**	0.1049**	0.0578**	0.1770**	0.2343**	0.1107**
Low sentiment	0.1245**	0.1538**	0.4809**	0.0933**	0.1065**	0.1499**	0.4242**	0.0968**
High sentiment	0.0480**	0.0223**	0.1919**	0.0133**	0.0495**	0.0847**	0.2022**	0.0556**
Low vs. normal	**0.0691****	−0.0141	**0.2474****	−0.0117	**0.0487****	−0.0271*	**0.1899****	−0.0139
High vs. normal	**−0.0075****	−0.1456**	**−0.0417****	−0.0916**	**−0.0084****	−0.0923**	**−0.0321****	−0.0551**

(continued)

Table 3 (*continued*)

	Investor Intelligence sentiment index				AAII sentiment index			
	E-mini S&P 500		E-mini Nasdaq-100		E-mini S&P 500		E-mini Nasdaq-100	
	R_t equation	F_t equation	R_t equation	F_t equation	R_t equation	F_t equation	R_t equation	F_t equation
Coefficients on returns								
"Normal" days	−0.1610**	14.61**	−0.1309**	3.55**	−0.1433**	13.18**	−0.1207**	3.39**
Low sentiment	−0.1400**	6.87**	−0.1027**	1.79**	−0.1289**	7.73**	−0.1004**	1.94**
High sentiment	−0.3246**	26.23**	−0.2605**	6.28**	−0.2533**	21.36**	−0.1983**	5.09**
Low vs. normal	0.0210	**−7.74****	0.0281**	**−1.76****	0.0143	**−5.46****	0.0202	**−1.44****
High vs. normal	−0.1635**	**11.61****	−0.1296**	**2.73****	−0.1101**	**8.18****	−0.0777**	**1.71****
Adjusted R^2	0.35	0.50	0.26	0.44	0.31	0.46	0.24	0.41
DW statistic	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00

*,** indicate that the null hypothesis of a Wald test for the sum of coefficients being equal to zero is rejected at 5% and 1% levels, respectively.

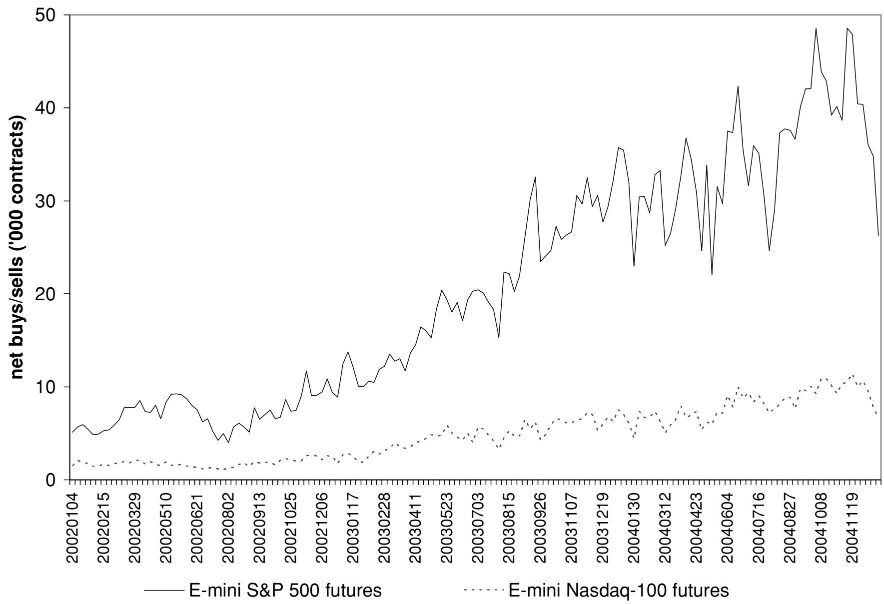


Figure 3

Feedback trading over time

The graph shows time variation in the cumulative effect of a 1% return shock on the order flow.

CF_t is the cumulative impulse response of the order flow (in thousands of contracts) after a unit return shock. The impulse responses are calculated separately for each week t. $Sentiment_t$ is the value of the investor sentiment index, and $Volume_t$ is the trading volume in the particular E-mini futures contract during week t (in millions of contracts). The trading volume is included as a regressor to control for a possible increase in the feedback trading explained by the overall increase in the trading activity in the E-mini markets. The model also includes a quadratic trend. A nonlinear trend in feedback trading is apparent in Figure 3. The regression in Equation (3) is estimated using OLS with the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance matrix.

The results in Table 4 appear to corroborate the subsample VAR results, showing that positive feedback trading increases during periods of bullish sentiment, controlling for time trend and changes in overall trading activity. The coefficient estimates of sentiment are positive and statistically significant in all cases. These coefficient estimates are smaller when the AAII sentiment index is used, possibly due to the higher overall variability in this sentiment measure.[7] The coefficients of the trend

[7] The difference between the coefficients of the two investor sentiment measures becomes much smaller if we standardize the two measures by dividing them by their sample standard deviations.

Table 4

Estimates of the effect of sentiment on feedback trading

The estimated coefficients are for the regression:

$$CF_t = \alpha + \beta_1 \, Sentiment_t + \beta_2 t + \beta_3 t^2 + \beta_4 \, Volume_t + \varepsilon_t.$$

CF_t is the cumulative impulse response of the order flow (in thousands of contracts) after a unit return shock. The impulse responses are calculated separately for each week t, as discussed in Section 4.2. $Sentiment_t$ is a measure of investor sentiment during week t, and $Volume_t$ is the trading volume in the particular E-mini futures contract (in millions of contracts) during week t. The sample period is from January 1, 2002 through December 30, 2004. The sample contains 156 weekly observations. The regression is estimated using OLS with the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance matrix. The coefficients of primary interest are shown in bold. Absolute values of t-statistics are in parentheses.

	E-mini S&P 500	E-mini Nasdaq-100
Panel A: With Investor Intelligence sentiment index		
Intercept	−9.63 (2.77)***	−1.79 (2.96)***
Sentiment	**21.97 (4.85)*****	**4.66 (6.17)*****
t	20.26 (3.75)***	2.58 (2.34)**
t^2	17.34 (2.72)***	5.93 (4.28)***
Trading volume	−0.10 (0.17)	0.20 (0.44)
Adjusted R^2	0.91	0.92
Panel B: With AAII sentiment index		
Intercept	−3.21 (1.26)	−0.27 (0.48)
Sentiment	**11.76 (4.53)*****	**2.17 (5.09)*****
t	23.92 (5.16)***	3.33 (3.05)***
t^2	15.35 (2.60)***	5.57 (4.12)**
Trading volume	−0.20 (0.36)	0.17 (0.38)
Adjusted R^2	0.92	0.92

*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

terms are positive and statistically significant, indicating an overall increase in positive feedback trading over our sample period.

To examine the relation between informativeness of order flow and investor sentiment, we estimate the regression:

$$CR_t = \alpha + \beta_1 \, Sentiment_t + \beta_2 t + \beta_3 t^2 + \beta_4 \, Volume_t + \varepsilon_t, \tag{4}$$

where CR_t is the cumulative impulse response of returns after a 1,000-contract shock from the order flow. These cumulative impulse responses measure the information content of trades. Similar to Equation (3), the regression also includes a quadratic time trend and the trading volume in the particular E-mini market.

The results are in Table 5. The coefficient β_2 is negative and statistically significant in all cases, suggesting an overall decline in the information content of order flow across the sample period. This decline could be related to increasing liquidity in the E-mini markets. Consistent with Hypothesis 3, the coefficient of the investor

Table 5

Estimates of the effect of sentiment on informativeness of order flow

The estimated coefficients are for the following regression:

$$CR_t = \alpha + \beta_1\ Sentiment_t + \beta_2 t + \beta_3 t^2 + \beta_4\ Volume_t + \varepsilon_t.$$

CR_t is the cumulative impulse response of returns after a 1,000-contract shock from the order flow. The impulse responses are calculated separately for each week t, as discussed in Section 4.2. $Sentiment_t$ is a measure of investor sentiment during week t, and $Volume_t$ is the trading volume in the particular E-mini futures contract (in millions of contracts) during week t. The sample period is from January 1, 2002 through December 30, 2004. The sample contains 156 weekly observations. The regression is estimated using OLS with the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance matrix. The coefficients of primary interest are shown in bold. Absolute values of t-statistics are in parentheses.

	E-mini S&P 500	E-mini Nasdaq-100
Panel A: With Investor Intelligence sentiment index		
Intercept	0.40 (9.47)***	1.39 (8.83)***
Sentiment	**−0.27 (3.82)*****	**−0.90 (3.55)*****
t	−0.44 (5.90)***	−1.37 (6.85)***
t^2	0.25 (4.32)***	0.72 (4.52)***
Trading volume	0.01 (0.90)	0.02 (0.70)
Adjusted R^2	0.81	0.88
Panel B: With AAII sentiment index		
Intercept	0.27 (10.74)***	1.06 (12.50)***
Sentiment	**−0.07 (2.18)****	**−0.36 (3.07)*****
t	−0.53 (6.53)***	−1.53 (6.84)***
t^2	0.30 (4.99)***	0.79 (4.53)***
Trading volume	0.01 (1.43)	0.03 (0.85)
Adjusted R^2	0.78	0.85

***, **, * indicate statistical significance at the 0.01, 0.05 and 0.10 level, respectively.

sentiment index is negative for both markets and both sentiment measures, which implies that order flow tends to be less informative in bullish periods.

4.3. Effect of investor sentiment on transitory volatility

To test Hypothesis 4, relating to the relation between investor sentiment and transitory volatility, we estimate transitory volatility using the variance decomposition approach of Hasbrouck (1993). The underlying model of the security price is:

$$p_t = m_t + s_t, \tag{5}$$

$$m_t = m_{t-1} + w_t. \tag{6}$$

The random walk component m_t is the "efficient price" that represents a conditional expectation of the security's terminal value. The pricing error s_t represents the deviation from the efficient price. It is driven by market frictions and noise trading. The variance of the pricing error is a natural measure of transitory volatility.

We estimate the pricing error variance using Hasbrouck's (1993) model. Specifically, we estimate the following VAR with four Equations:

$$\begin{bmatrix} r_t \\ \mathbf{x}_t \end{bmatrix} = \sum_{i=1}^{k} A_i \begin{bmatrix} r_{t-i} \\ \mathbf{x}_{t-i} \end{bmatrix} + \begin{bmatrix} v_{rt} \\ \mathbf{v}_{xt} \end{bmatrix}, \tag{7}$$

where r_t are returns based on trade prices and $\mathbf{x}_t$ is a vector of three variables: (1) a variable representing signed trades (equal to one for buys and minus one for sells), (2) signed trade volume and (3) signed square root of the trade volume. A_i are coefficient matrices and v_t are serially uncorrelated innovations with a covariance matrix cov(v). In contrast to the VAR model used to examine feedback trading, this model includes no contemporaneous returns or signed volumes and uses no time aggregation, i.e., the subscript t indexes transactions. The trade-by-trade returns are computed without correction for the bid-ask bounce. We estimate the VAR separately in each weekly interval in our sample using 10 lags of all variables in the model.[8]

Hasbrouck (1993) shows that the pricing error in Equation (5) can be estimated as:

$$s_t = \sum_{j=0}^{\infty} \alpha_j v_{r,t-j} + \sum_{j=0}^{\infty} \beta_{1j} v_{x1,t-j} + \sum_{j=0}^{\infty} \beta_{2j} v_{x2,t-j} + \sum_{j=0}^{\infty} \beta_{3j} v_{x3,t-j}. \tag{8}$$

Intuitively, the pricing error is driven by temporary impacts of innovations in returns and trades, as well as by lagged adjustment to information. The α and β coefficients in Equation (8) are obtained from a vector moving average (VMA) representation of the VAR in Equation (7). We obtain the VMA coefficients from impulse responses and estimate the variance of the pricing error for each weekly interval as[9]:

$$\sigma_s^2 = \sum_{j=0}^{\infty} [\, \alpha_j \;\, \beta_j \,] \mathrm{cov}(v) \begin{bmatrix} \alpha_j \\ \beta_j' \end{bmatrix}. \tag{9}$$

To examine the relation between transitory volatility and investor sentiment, we consider the following regression:

$$\sigma_{st}^2 = \alpha + \beta_1 Sentiment_t + \beta_2 t + \beta_3 t^2 + \beta_4 Volume_t + \beta_5 \sigma_t^2 + \varepsilon_t, \tag{10}$$

where σ_t^2 is the variance of daily returns on the index underlying the particular E-mini contract, estimated with a GARCH(1,1) model and sampled on the days when Investor Intelligence releases its sentiment measures. The sentiment in this model can be viewed as a proxy for noise trading activity. Investor sentiment may be correlated with transitory volatility because it is correlated with the overall return volatility,

[8] The regression results discussed below are not affected qualitatively by the number of lags in the VAR.

[9] Hasbrouck (1993) shows that this expression represents the lower bound of σ_s^2. The actual value of the pricing error variance may exceed the lower bound due to factors uncorrelated with lagged returns and signed trades.

Table 6

Estimates of the effect of sentiment on transitory volatility

The estimated coefficients are for the following regression:

$$\sigma_{st}^2 = \alpha + \beta_1 Sentiment_t + \beta_2 t + \beta_3 t^2 + \beta_4 Volume_t + \beta_5 \sigma_t^2 + \varepsilon_t.$$

σ_{st}^2 is the variance of the pricing error (transitory volatility) estimated separately for each week t, as discussed in Section 4.3. $Sentiment_t$ is a measure of investor sentiment during week t, $Volume_t$ is the trading volume in the particular E-mini futures contract (in millions of contracts) during week t, and σ_t^2 is the variance of daily returns on the index underlying the particular E-mini contract, estimated with a GARCH(1,1) model. The sample period is from January 1, 2002 through December 30, 2004. The sample contains 156 weekly observations. The regression is estimated using OLS with the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance matrix. All coefficients are multiplied by 10^5. The coefficients of primary interest are shown in bold. Absolute values of t-statistics are in parentheses.

	E-mini S&P 500	E-mini Nasdaq-100
Panel A: With Investor Intelligence sentiment index		
Intercept	6.78 (6.86)***	14.01 (6.18)***
Sentiment	**−7.19 (4.95)***	**−18.14 (6.47)***
t	5.64 (4.25)***	12.32 (6.70)***
t^2	−6.17 (5.56)***	−12.20 (7.24)***
Trading volume	0.28 (1.86)*	0.11 (0.32)
Daily volatility	0.47 (3.67)***	0.89 (8.48)***
Adjusted R^2	0.79	0.90
Panel B: With AAII sentiment index		
Intercept	3.44 (5.81)***	4.70 (3.28)***
Sentiment	**−2.30 (3.53)***	**−5.96 (4.18)***
t	3.99 (3.06)***	10.86 (5.22)***
t^2	−4.91 (4.84)***	−10.81 (5.76)***
Trading volume	0.33 (1.92)*	0.31 (0.78)
Daily volatility	0.66 (5.62)***	1.14 (10.70)***
Adjusted R^2	0.77	0.87

***, **, * indicate statistical significance at the 0.01, 0.05 and 0.01 level, respectively.

and the return volatility is correlated with transitory volatility. We include the return volatility in the regression to test whether sentiment-driven trading affects the variance of the pricing error for a given return volatility.

The regression estimates are in Table 6. As expected, the results show a strong positive relation between the variance of the pricing error and return volatility. Rejecting Hypothesis 4, the coefficient of sentiment is also statistically significant and negative for both E-mini markets and both sentiment measures, suggesting that index futures prices tend to follow the underlying efficient price more closely in bullish periods, consistent with increased liquidity in bullish states (e.g., Baker and Stein, 2004).

The lower variance of the pricing error in periods of high investor sentiment is not inconsistent with the reduced information content of order flow in the previous subsection. Increased liquidity trading in high-sentiment states can simultaneously lead to lower average information content of trades and lower transitory volatility.

Hasbrouck (1993, p. 196) notes that empirical microstructure models that only account for very high-frequency serial dependencies, such as the VAR model used to estimate the pricing error variance, tend to impound low-frequency transitory components of prices into the "efficient price." Therefore, it is possible that transitory volatility observed at intraday frequencies declines in periods of high investor sentiment, whereas, as Brown and Cliff (2005) show, long-horizon pricing errors increase.[10]

4.4. Robustness checks

A potential concern in regressions using levels of economic time series is the spurious regression problem discussed by Granger and Newbold (1974). When two independent nonstationary variables are regressed on each other, the results may suggest a significant relation between the two variables. We use Augmented Dickey-Fuller and Phillips-Perron unit root tests to test the stationarity of the investor sentiment measures and the dependent variables in our regressions. An intercept and a linear trend are included in the test equation. In all cases, with the exception of transitory volatility in the E-mini Nasdaq-100 market, the null of the unit root is rejected by one or both of the tests. When the unit root tests are repeated for residuals from regressions of the two sentiment measures and the three dependent variables on a quadratic trend, the null of the unit root is rejected by both tests at the 1% level in all cases. These results indicate that our variables are trend-stationary.

In a spurious regression, the error term is nonstationary (e.g., Stock and Watson, 1988, p. 166). We examine residual autocorrelations and test for the unit root in the residuals for all our regressions. The first-order serial correlation of regression residuals never exceeds 0.7 and the null hypothesis of unit root in the residuals is rejected in all cases, suggesting that the results are not affected by the spurious regression problem. Furthermore, the results of the regression tests of Hypotheses 2 and 3 are supported by the subsample VAR results reported in Table 3.

To explicitly account for serial correlation in the regression residuals, we also estimate the regressions in Equations (3), (4), and (10) using maximum likelihood with AR(1) residuals. The results are qualitatively similar to the OLS results. Since OLS estimation could be sensitive to the presence of outliers, we also estimate the regressions using the weighted least squares procedure introduced by Yohai (1987). This procedure maintains robustness in the presence of a large number of outliers. The results again are qualitatively similar to the OLS results. Finally, we experiment with two additional proxies for investor sentiment: the UBS/Gallup Index of Investor Optimism and the forward P/E ratio of the S&P 500 index .[11] Both measures are

[10] Brown and Cliff (2005) estimate pricing errors for the aggregate stock market using monthly data.

[11] Fisher and Statman (2006) use the P/E ratio of the S&P 500 index as an indirect measure of sentiment.

available monthly. The regression results are qualitatively similar. The robustness checks are not reported in detail but are available from the author.

5. Conclusion

This paper examines how the order flow of traders in index futures markets is affected by recent price changes. We show that index futures traders use positive feedback trading strategies, i.e., they buy index futures contracts after price increases and sell after price declines. Such positive feedback trading has become more prevalent in index futures markets in recent years. We also find a positive relation between intensity of the positive feedback trading and investor sentiment. This result suggests that positive feedback trading consists, at least in part, of sentiment-driven noise trading.

Consistent with the noise trading hypothesis, we find that order flow contains less information in periods of bullish sentiment. Finally, we find a strong negative relation between the variance of the pricing error estimated at intraday frequencies and investor sentiment measures. This finding implies that sentiment-driven trading increases market liquidity, helping to stabilize temporary price fluctuations. Overall, this paper provides new evidence on the link between investor attitudes, trading behavior and price efficiency at the microstructure level.

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