Overnight returns, daytime reversals, and future stock returns

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ABSTRACT

A higher frequency of positive overnight returns followed by negative trading day reversals during a month suggests a more intense daily tug of war between opposing investor clienteles, who are likely composed of noise traders overnight and arbitrageurs during the day. We show that a more intense daily tug of war predicts higher future returns in the cross section. Additional tests support the conclusion that, in a more intense tug of war, daytime arbitrageurs are more likely to discount the possibility that positive news arrives overnight and thus overcorrect the persistent upward overnight price pressure.

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1. Introduction

An emerging literature establishes that many stocks and portfolios display systematic return patterns across the daily trading cycle.[1] In particular, there is a well-documented tendency for reversals between successive overnight and trading day periods. According to Lou, Polk, and Skouras (2019, hereafter LPS), two distinct clienteles tend to dominate the overnight and daytime trading sessions, and persistent excess demand by these respective groups of investors can create a daily "tug of war" that leads to a recurring pattern of return reversals across the two periods. For instance, excess demand by the prevailing overnight clientele may tend to pull prices in one direction, which culminates in an opening price that is at odds with the views of the opposing clientele. As a result, this opposing clientele may pull prices back through daytime trading, culminating at the day's close in a trading day reversal.

Prior work establishes that investor heterogeneity has significant implications for asset prices.[2] The possibility that heterogeneous investor clienteles may persistently dominate the respective overnight and trading day periods raises the question of whether the presence and intensity of their daily tug of war might affect asset prices over time. A natural indicator of the intensity of this tug of war between overnight and trading day clienteles is the frequency of daily return reversals during a month. In this paper, we construct two measures of the intensity of this

[1] See Abdi (2019), Aboody, Even-Tov, Lehavy, and Trueman (2018), Berkman, Koch, Tuttle, and Zhang (2012), Bogousslavsky (2016, 2020), Branch and Ma (2012), Cliff, Cooper, and Gulen (2008), Hendershott, Livdan, and Rösch (2020), Heston, Korajczyk, and Sadka (2010), Lou, Polk, and Skouras (2019), and Miller (1989). Prior research also examines price discovery after trading hours (Barclay and Hendershott, 2003).

[2] For example, see Campbell (2003), Chabakauri (2013), Chan and Kogan (2002), Christensen, Larsen, and Munk (2012), Cochrane (2017), Constantinides and Duffie (1996), Gârleanu and Panageas (2015), Grossman and Zhou (1996), and Harrison and Kreps (1978).

tug of war for a given stock by computing the abnormal frequency of daily reversals in a month that are characterized by either low or high opening prices. We then examine whether either of these two measures contains predictive information about future stock returns.

We find that the monthly intensity of this daily tug of war predicts returns in the cross section, but only when daily reversals are characterized by high opening prices. That is, stocks with a high frequency of positive overnight returns followed by negative daytime reversals in month *t* outperform stocks with a low frequency of such reversals, by 0.92% in month *t*+1. In contrast, we find no such predictive relation when there is a high frequency of negative overnight returns followed by positive daytime reversals (i.e., reversals characterized by low opening prices). We also find that the return predictability we show is driven by overnight returns during month *t*+1, rather than daytime returns. Our results are robust when we consider various methods to adjust for risk, alternative sets of control variables, different sample periods or listing exchanges, and alternative definitions of opening and closing prices to measure overnight and daytime returns. They also remain robust when we exclude months with earnings announcements, skip a month between portfolio formation and holding periods, and perform an out-of-sample test on NYSE stocks from 1926 to 1962.

We explore the underlying economic mechanism behind these results by considering potential sources of the opposing price pressure during the overnight and trading day periods. On the one hand, a high frequency of positive overnight returns that are reversed during the next trading day may indicate ongoing efforts by daytime arbitrageurs to offset repeated upward overnight price pressure by uninformed noise traders. This view is in line with recent work suggesting that individual and institutional investors represent two investor clienteles that cause persistent opposing price pressure during respective overnight and trading day periods.[3]

On the other hand, not all variation in overnight returns is due to uninformed demand. While price discovery generally occurs during the trading day, a significant amount of price discovery also occurs during the overnight period, since firms disclose a substantial amount of material public information after the market closes (Barclay and Hendershott, 2003; Santosh, 2016). Hence, any association between a more intense tug of war and future returns should depend on the ability of daytime arbitrageurs to distinguish the portion of recurring positive overnight returns that is based on noise trading from the portion that is due to new information.

We conjecture that the return predictability we show can be explained by a tendency for daytime arbitrageurs to overcorrect a prolonged sequence of positive overnight returns, as they come to overweight the role of noise traders behind this price pressure and underweight its potential information content. As a tug of war progresses across more days, daytime arbitrageurs may discount the possibility that the succession of positive overnight returns could be due to the arrival of positive information, rather than just overly optimistic noise trading. As a result, they may reduce their ongoing efforts to diligently analyze potential sources of information behind the positive overnight returns. This inclination could reduce the quality of their decision-making over time and thus their ability to distinguish the portion of overnight returns due to noise versus that due to positive information. Consequently, they may continue to trade against this overnight price pressure without rigorously analyzing its information content. Over time, this behavior

[3] For example, LPS find that individual investors are inclined to initiate trades overnight and near the open, while institutional investors are likely to trade in the opposite direction throughout the trading day. Berkman, Koch, Tuttle, and Zhang (2012) find evidence suggesting that overnight buying by individual investors tends to cause upward price pressure at the open that is reversed during the day, presumably by institutional trading.

could result in overcorrection such that the stock becomes undervalued (since only the portion of overnight price run-ups that is due to uninformed noise trading should be corrected).[4]

Our finding of positive expected returns for stocks engaged in a prolonged tug of war suggests that not all variation in a persistent sequence of positive overnight returns is due to uninformed demand. Rather, we conjecture that some component of repeated overnight price pressure tends to be based on superior information relative to the behavior of daytime arbitrageurs. When evaluated in terms of the fundamental value of the stock revealed by future monthly returns, daytime arbitrageurs tend to be on the wrong side of a more intense tug of war. This argument seems at odds with prior findings that emphasize rational trading by daytime arbitrageurs and irrational behavior associated with overnight retail traders.[5]

We begin by documenting three asymmetric findings that support the overcorrection hypothesis. First, persistent daily reversals with high opening prices predict returns, but reversals with low opening prices do not. High opening prices may reflect price pressure by optimistic

[4] While arbitrageurs are generally considered to be sophisticated investors who correct mispricing, there is also evidence that they may cause inefficiency in the market. For example, Stein (2009) argues that arbitrageurs sometimes cause prices to deviate from fundamentals. Similarly, Kahneman and Egan (2011) and Stanovich and West (2000) argue that judgments made under pressure, distraction, or fatigue tend to be made heuristically. Consistent with this view, Hirshleifer, Levi, Lourie, and Teoh (2019) find that, on days when a high number of analyst forecasts are released, more analysts resort to heuristic decision-making by relying on their own previous forecasts or the forecasts of other analysts. See also Allen and Gale (2005), Brunnermeier and Pedersen (2008), Edelen, Ince, and Kadlec (2016), Gromb and Vayanos (2002), Kyle and Xiong (2001), Morris and Shin (2004), and Shleifer and Vishny (1997).

[5] For example, see Aboody, Even-Tov, Lehavy, and Trueman (2018), Berkman, Koch, Tuttle, and Zhang (2012), Bogousslavsky (2020), Gromb and Vayanos (2010), and LPS.

overnight retail traders who can collectively buy stocks that attract their attention. In contrast, pessimistic overnight retail traders cannot sell stocks if they do not own them, since they typically do not sell short (Barber and Odean, 2008; Berkman et al., 2012; Odean, 1999). Furthermore, during the overnight period short selling is expensive and risky, so there should be less arbitrage activity to counteract optimistic traders (Bogousslavsky, 2020). Thus, while optimistic noise traders can cause overvaluation overnight and at the open, pessimistic noise traders are less likely to cause undervaluation overnight. This asymmetric role of overnight noise traders increases the likelihood that daytime arbitrageurs will attribute recurring positive overnight returns to noise rather than new information, in contrast to negative overnight returns. As a result, daytime traders are more likely to overcorrect a series of positive overnight returns.

Second, the return predictability we show is concentrated among the stocks in the long leg of the trading strategy, not the short leg. According to our conjecture, daytime arbitrageurs tend to overcorrect positive overnight returns when a tug of war is more intense, so the subset of stocks with a high frequency of negative daytime reversals should be undervalued and thus have higher future returns. In contrast, a low frequency of negative daytime reversals indicates a month with a less intense tug of war, so daytime arbitrageurs are less likely to overcorrect and return predictability should be weaker. This finding that the return predictability is concentrated among the stocks in the long leg of the hedge portfolio further supports the overcorrection hypothesis.

Third, we conduct a placebo test in which we analyze the alternative sequence of daily reversals that proceed from a negative daytime return to a positive overnight reversal, rather than the other way around. These alternative daytime-to-overnight positive reversals are unrelated to our conjecture that daytime arbitrageurs respond to and overcorrect persistent positive overnight returns. As expected, we find no predictive power behind these daytime-to-overnight positive reversals. This placebo test establishes that only the sequence of intraday reversals in which daytime arbitrageurs respond to positive overnight returns leads to the return predictability we show, further reinforcing the overcorrection hypothesis.

We conduct several additional tests to further investigate our conjecture. First, we examine the implications of our overcorrection hypothesis for the identity of traders who participate in a tug of war. If a higher frequency of positive overnight returns and negative daytime reversals truly reflects a more intense tug of war between overnight noise traders and daytime arbitrageurs, then we should observe a greater presence of both buying by retail investors and short selling by arbitrageurs together in the marketplace. Consistent with this view, we show that a higher frequency of positive overnight returns and negative daytime reversals is indeed associated with both greater retail buying and elevated short selling in the same month.

Second, we analyze intraday trading patterns by arbitrageurs studied in prior work, which further support the overcorrection hypothesis. Arbitrageurs who trade on perceived overpricing at the open should enter their short positions early in the day to maximize profits. Furthermore, according to Bogousslavsky (2020), lending fees and overnight risk incentivize some arbitrageurs to close their short positions by the end of the trading day. If more daytime arbitrageurs act in this fashion, then the hypothesized overcorrection (i.e., the negative daytime returns in a prolonged tug of war) should mainly occur in the earlier portion of the average trading day. Consistent with this argument, we find that the average negative daytime reversal for the subset of "tug-of-war days" with positive overnight returns and negative daytime reversals arrives more in the early portion of the trading day and less in the latter part of the day. Furthermore, if arbitrageurs tend to slow down their short selling activity or reverse their short positions late in the day, then the hypothesized overcorrection should be mitigated and the predictive relation should become weaker. Indeed, we show that, for stocks with a negative daytime reversal that is mitigated in the latter portion of the trading day, the predictive relation does become weaker.

Third, during a prolonged tug of war, overcorrection by daytime arbitrageurs should be more pronounced among stocks that are more difficult to analyze and subject to greater information uncertainty. Consistent with this view, our results are stronger for firms with small size, high idiosyncratic volatility, low liquidity, and low analyst coverage. These firms have greater information uncertainty and are more likely to be affected by speculative noise trading (Baker and Wurgler, 2006).

Fourth, overcorrection of positive overnight returns by daytime investors should lead to relatively lower stock returns in the same month. In support of this view, we find significantly lower contemporaneous returns during months with a higher abnormal frequency of positive overnight returns and negative daytime reversals.

Fifth, we examine the role of public news behind our findings. If daytime traders are prone to ignore positive news that may arrive either overnight or during the day in a persistent tug of war, this behavior could lead to overcorrection of the overnight price pressure. Using Thomson Reuters news feeds, we find that the subset of tug-of-war days with positive overnight returns and negative daytime reversals has an average measure of news sentiment that is positive for the overnight period and even more positive for the trading day. This outcome suggests that, on these tug-of-war days, daytime traders tend to ignore positive public news that arrives either overnight or during the day.

Sixth, we examine whether a more intense tug of war predicts firm fundamentals. We find that stocks with a higher frequency of positive overnight returns and negative trading day reversals tend to have a larger earnings surprise at the next earnings announcement. This outcome further supports the view that, in a more intense tug of war, daytime arbitrageurs tend to disregard or underreact to positive information about the firm's future fundamentals.

We also explore several potential alternative explanations to our theory that daytime arbitrageurs tend to overcorrect in a prolonged tug of war. These alternatives include possible overvaluation in month t+1, a risk premium for greater disagreement between overnight and daytime investor clienteles, and a premium for arbitrage risk associated with trading against noise traders or with holding positions overnight. In each case, the evidence is contrary to the alternative explanation and is more consistent with overcorrection by daytime arbitrageurs.

Finally, we examine the time-varying predictive power of the abnormal intensity of a tug of war across periods of high versus low market sentiment, because the prior literature shows that sentiment plays an important role in affecting retail investor behavior and market mispricing (e.g., Aboody et al., 2018; Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan, 2012). We find that this return predictability is significantly stronger during high sentiment periods. This finding supports the argument that, when sentiment is high, daytime arbitrageurs have a greater tendency to assume that a prolonged sequence of positive overnight returns is due to noise trading. As a result, they are more likely to attribute overnight price pressure to uninformed retail traders in an ongoing tug of war, resulting in greater overcorrection and a stronger predictive relation.

2. Literature review

This paper contributes to several strands of literature. First, we add to the emerging work on positive overnight returns and negative daytime reversals. LPS find that these overnight and daytime components of daily stock returns are persistent, which they attribute to a recurring tug of war between opposing groups of investors who trade at different times of the day. Berkman et al. (2012) argue that these persistent daily reversals are likely due to high opening prices caused by retail investors who buy attention-grabbing stocks overnight or at the open. Aboody et al. (2018) show that persistent overnight returns are consistent with prior evidence of short-term persistence in demand by sentiment-influenced investors. Our paper is the first to uncover a link between the intensity of this daily tug of war and future returns, and to provide further evidence regarding how this tug of war is associated with market efficiency.

This work is also related to the literature showing that unconditional average returns are lower for speculative stocks (Baker and Wurgler, 2006; Miller, 1977). This literature argues that, in the presence of short sale constraints, arbitrageurs stay by the sidelines, so stock prices are determined by optimistic traders.[6] This theory offers a static mechanism that produces overvalued stocks, so future returns should be lower, especially for speculative stocks that are subject to overpricing by optimistic noise traders during periods of high sentiment. In this static setting, one might expect that a more intense tug of war should make these speculative stocks overpriced, so that they earn lower (not higher) returns in the future.

However, our setting is a dynamic one, where arbitrageurs who operate during the day repeatedly battle against optimistic noise traders who dominate overnight trading. In this setting, a succession of positive overnight returns and negative daytime reversals could manifest repeated daily price corrections, as suggested by Berkman et al. (2012) and LPS. In contrast to Miller's (1977) theory, we argue that a more intense daily tug of war leads arbitrageurs to overcorrect the

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[6] Among others, see Berkman, Dimitrov, Jain, Koch, and Tice (2009), Berkman, Koch, Tuttle, and Zhang, (2012), Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), and Stambaugh, Yu, and Yuan (2012).

positive overnight price pressure over time, by overweighting the noise component in the succession of positive overnight returns, and thereby making the stock undervalued.

3. Data, variables, and sample statistics

Our sample includes the common shares (share codes 10 and 11) for all NYSE, AMEX, and NASDAQ stocks from CRSP. We match stock prices from CRSP with annual accounting data that are at least six months old (i.e., covering the previous seven to 18 months) from Compustat. We exclude financial and utility firms and restrict the sample to firm-month observations with previous month-end stock prices above one dollar. The sample extends from May 1993 through December 2017.[7]

3.1. Measuring the intensity of a daily tug of war

We capture variation in the intensity of a daily tug of war using two measures: the abnormal frequency of negative or positive daytime reversals.[8] We first decompose daily stock returns into their respective overnight and daytime components, following LPS. Specifically, for each firm *i* on day *d*, we define the daytime (open-to-close) return as the relative price change from the market open to the close on day *d*, $\mathrm{RET\_OC_{id}} = \frac{\mathrm{P_{id}^{Close}}}{\mathrm{P_{id}^{Open}}} - 1$. We then impute the previous overnight (close-to-open) return from the daytime return and the daily close-to-close return ($\mathrm{RET_{id}}$), as $\mathrm{RET\_CO_{id}} = \frac{1+\mathrm{RET_{id}}}{1+\mathrm{RET\_OC_{id}}} - 1$. We define a negative (or positive) daytime reversal as a positive (or negative) overnight return that is followed by a negative (or positive) daytime return.

[7] Our sample starts in May 1993 because daily opening prices are available from CRSP since July 1992, and we require ten months of non-missing data in the previous 12 months to construct our main variable of interest.

[8] We aggregate days with overnight-trading day reversals over a month to reduce the effect of noise, while capturing periods of intensified activity by opposing clienteles. Direct analysis of daily reversals produces similar results.

We next calculate the ratio of the number of days with negative (or positive) reversals to the total number of trading days during month *t*, and we denote this variable as NR_{it} (or PR_{it}). These two frequency measures reflect the *level of intensity* in a daily tug of war for firm *i* during month *t*, involving either negative or positive daytime reversals. Finally, our main variable of interest is the *abnormal level of intensity* in the tug of war, defined as the abnormal frequency of negative daytime reversals (AB_NR_{it}), which is NR_{it} scaled by the average NR_{it} over the prior 12 months. The abnormal frequency of positive daytime reversals (AB_PR_{it}) is defined similarly.

We focus on the *abnormal* frequency of daytime reversals rather than the *level* itself. As discussed above, our goal is to understand whether variation in the monthly intensity of a daily tug of war contains predictive information about future stock prices. However, as shown by LPS, the overnight and daytime components of daily returns in an ongoing tug of war may persist for up to five years. Over such a long period, this lingering persistence could mask any potential information about future prices that is temporarily embodied in a more intense tug of war.

Moreover, in the context of our overcorrection hypothesis, it is unlikely that a subset of optimistic overnight traders would continue to trade on superior information relative to daytime arbitrageurs over such a long period. Thus, it is also unlikely that daytime arbitrageurs would continue to overcorrect such normal persistence in positive overnight returns for such a long time, or that all such months would be equally likely to promise higher future returns. Therefore, we argue that a high *abnormal* frequency of reversals can better capture an increase in the intensity of this ongoing tug of war and thus identify periods when daytime arbitrageurs are more likely to overcorrect.[9]

[9] Despite this economic rationale for relying on the abnormal level, we repeat our main analysis using the actual level of reversals (NR or PR) and find similar results, provided in Table A.2 of the Internet Appendix.

3.2. Descriptive statistics for the tug-of-war measures

In this section, we provide summary statistics for our two measures of the *abnormal level of intensity* in a tug of war (i.e., AB_NR and AB_PR). We also provide analogous statistics for the *level of intensity* in a tug of war (i.e., NR and PR). Panel A of Table 1 presents time series averages of the monthly cross-sectional summary statistics for these four variables. Our main variable of interest, the abnormal frequency of negative reversals (AB_NR), has a mean close to 1, indicating that the typical monthly frequency of negative reversals (NR) is close to its own moving average from the prior 12 months. On the other hand, there is substantial variation in AB_NR, ranging from 0.00 to 4.08, which corresponds to a 100% decline versus a 408% increase in the abnormal frequency of negative daytime reversals for a given month. We find similar patterns for the abnormal frequency of positive reversals (AB_PR).

In addition, the mean *level of intensity* in a tug of war (i.e., the frequency of negative reversals, NR) is 25%, indicating that one-fourth of the trading days in a typical month have a positive overnight return followed by a negative daytime reversal. Similar results apply to the frequency of positive reversals (PR), with a mean of 24%. At first glance, this evidence appears to suggest that these two alternative sets of daily reversals occur randomly over time, as would be expected by chance if positive and negative returns were equally likely during respective overnight and intraday periods. However, there are not four, but five possible categories of overnight-daytime return patterns. The fifth group includes other days with a zero return for either the daytime or overnight period, or both, which occurs on 9% of all trading days. This observation establishes that these five possible groups of overnight-daytime return patterns do not occur randomly. Rather, tug-of-war days with a reversal across overnight and daytime trading periods (i.e., NR or PR) occur more frequently than the other three groups.[10]

In Panel B of Table 1, we provide the correlations across these tug-of-war measures. These correlations also reveal some interesting differences from a theoretical random sample of independent draws for these five types of possible trading days. For example, the Pearson correlation between NR and LeadNR (i.e., the value of NR in month t+1) is 0.20, which indicates significant persistence in the level of intensity for a tug of war involving positive overnight returns and negative daytime reversals. Likewise, there is significant persistence in the abnormal level of intensity for a tug of war, AB_NR (with a Pearson correlation of 0.10 between AB_NR and LeadAB_NR). Similar correlations also prevail between PR and LeadPR, and AB_PR and LeadAB_PR. Together, these results indicate that abnormal movements in the intensity of a tug of war during one month tend to spill over into the next month.

We further explore persistence in the abnormal intensity of a tug of war by regressing AB_NR (or AB_PR) in each of the next three months ($t+a$: a = 1 - 3) on AB_NR (or AB_PR) during month t with or without control variables. In Panel A (or Panel B) of Table 2, the coefficient of AB_NR (or AB_PR) is significantly positive in all columns, and this coefficient declines monotonically when we analyze persistence further into the future. These results provide further evidence that our proxies for an intensified tug of war are persistent across months, even though they reflect “abnormal” measures. Furthermore, the gradual decay of these coefficients further into the future suggests that an intensified tug of war does not last very long, on average.[11]

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[10] See also Table A.1 of the Internet Appendix.

[11] In Section A.1 of the Internet Appendix, we find stronger persistence when we consider an alternative benchmark to construct AB_NR, which skips one year and extends further back in time, from month t-24 to t-13 rather than

3.3. Other control variables

In our regression analysis, we control for various other firm characteristics that have also been shown to predict returns. We provide details regarding the construction of all variables in Appendix 1. Panel A of Table 3 presents time series averages of the monthly cross-sectional summary statistics for these other control variables in our main analysis, as well as the abnormal measures of a tug of war.[12]

Panel B provides the analogous time series means of the monthly cross-sectional correlations across these variables. The results show that the abnormal frequency of negative reversals (AB_NR) is inversely correlated with the firm's return in the same month (RET). Furthermore, AB_NR is positively related to the overnight component of monthly returns (RET_CO_M) and negatively related to the daytime component (RET_OC_M). This outcome is expected, indicating a tendency for months with a higher frequency of positive overnight returns followed by negative daytime reversals to reveal more of the firm's cumulative monthly return during the overnight period and less during the daytime. In contrast, AB_NR has low correlations with the other control variables, indicating that it offers novel information about the firm, beyond that provided by the other firm attributes.[13]

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from month *t*-12 to *t*-1. In addition, we also explore persistence in AB_NR and AB_PR by constructing transition matrices across consecutive months and find similar results (see Section A.2 of the Internet Appendix).

[12] Panel A of Table 3 shows that the monthly average of the maximum monthly close-to-close return (RET) is 1.94 (or 194%), which is large in magnitude. The same issue applies to RET_OC_M and RET_CO_M. We note that these extreme values are due to a few outliers. Our main results are robust when we exclude these outliers.

[13] AB_PR is positively related to the firm's return in the same month (RET), negatively related to the overnight component of monthly returns (RET_CO_M), and positively related to the daytime component (RET_OC_M). Like AB_NR, AB_PR also has low correlations with the other control variables.

4. Main analysis: The intensity of a daily tug of war and future stock returns

4.1. Fama-MacBeth regression approach

In this subsection, we present the results of Fama-Macbeth regression analysis with various subsets of control variables. In the first four columns of Table 4, the coefficient of AB_NR is significantly positive, ranging from 0.34 to 0.51 with *t*-values above 6.0. This evidence indicates that firms with a higher abnormal frequency of *negative* daytime reversals in month *t* have significantly higher returns in month *t*+1. In contrast, the abnormal frequency of *positive* daytime reversals (AB_PR) is never significant in Table 4. Together, this evidence indicates an asymmetric relation in which the abnormal frequency of negative daytime reversals predicts future stock returns, while positive daytime reversals do not.[14]

This asymmetric finding points toward an explanation based on overcorrection by daytime traders during a more intense tug of war comprised of positive overnight returns and negative daytime reversals. With high opening prices, daytime arbitrageurs are more likely to discount the possibility that positive overnight price pressure may be due to positive information and instead to attribute this price pressure to overly optimistic noise traders. As a result, they may come to overcorrect the sequence of positive overnight returns in such a prolonged tug of

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[14] The fifth column of Table 4 reveals that dropping AB_NR and AB_PR has little impact on the Fama-MacBeth mean adjusted R^2. Similarly, in an unreported analysis, we find that excluding any of these control variables, which are popular predictors of stock returns, also has a small impact on the Fama-MacBeth mean adjusted R^2. This result is consistent with prior literature, which generally finds that well-known anomalies explain very little variation in stock returns over time (Lewellen, 2015). Indeed, the overall adjusted R^2s in Table 4 are uniformly less than 5%.

war.[15]

4.2. Portfolio approach

4.2.1. Equally weighted portfolio returns and Fama-French alphas

In this subsection, we sort the cross section of stocks each month (*t*) into deciles based on AB_NR and hold each portfolio during the following month. Panel A of Table 5 reports the portfolio returns in month *t*+1. The top row of Panel A indicates that the highest decile based on AB_NR outperforms the lowest decile by an average monthly equal-weighted hedge portfolio return of 0.92% (*t*-ratio = 5.19). In the remaining two rows of Panel A, we show that these results are robust when we analyze the monthly risk-adjusted portfolio returns (alphas) from the Fama-French four-factor and six-factor models (Carhart, 1997; Fama and French, 2018).[16]

This analysis also documents a second important asymmetric finding by showing that the return predictability contained in AB_NR is concentrated among stocks in the long leg of the hedge portfolio (decile 10) rather than the short leg (decile 1). For example, Panel A of Table 5 reveals a Fama-French four-factor (or six-factor) alpha of 58 (or 62) basis points (bps) per month, with a *t*-ratio of 3.37 (or 3.52), for the highest decile based on AB_NR. In contrast, for the lowest decile, the analogous four-factor (or six-factor) alpha is smaller in magnitude and significance, at -0.23 (or -0.24) bps, with a *t*-ratio of -1.87 (or -1.92).

[15] In Table A.2 of the Internet Appendix, we show that the results in Table 4 are robust when we replace the abnormal frequency of each type of daily reversal (AB_NR and AB_PR) with the actual frequency (NR and PR). Since Table 4 shows that the abnormal frequency of *positive* daytime reversals (AB_PR) is unrelated to future returns, we only include the abnormal frequency of *negative* daytime reversals (AB_NR) in all remaining analyses. The predictive relation between AB_NR and returns remains robust when we include AB_PR in our other analyses.

[16] Our results are also robust when we use the three-factor and five-factor models (Fama and French, 1993, 2015).

This asymmetry further supports our conjecture that a high (not low) frequency of negative daytime reversals captures periods when daytime investors tend to overcorrect the succession of positive overnight returns. In contrast, an abnormally low frequency of negative reversals indicates a month in which daytime traders are less likely to overcorrect, so the return predictability should be weaker. This finding that the AB_NR hedge portfolio return is mainly driven by the long leg is also distinct from many other anomalies whose profits mainly come from the short leg of the hedge portfolio (e.g., see Stambaugh, Yu, and Yuan, 2012).

4.2.2. Value-weighted portfolio returns

In this subsection, we reproduce the portfolio analysis above using value-weighted portfolios. The results are presented in Panel B of Table 5. In this analysis, the value-weighted return difference between the highest and lowest AB_NR deciles is not significant at any acceptable level. This evidence indicates that a simple value-weighted portfolio strategy does not yield the significant return predictability that we find with equal-weighted portfolios.

An important concern regarding the value-weighted results in Panel B of Table 5 is that firm size is a highly skewed variable that places extraordinary influence on very large firms. To explore the extent to which these value-weighted results are driven by a few extremely large stocks, we exclude the top 1% of stocks by firm size each month and then repeat the value-weighted portfolio analysis with the remaining stocks. We present the results in Panel C of Table 5. Now the mean value-weighted difference in raw returns between the top and bottom deciles by AB_NR is 49 basis points per month, which is significant at the 1% level (*t*-value = 3.03). We obtain similar results for Fama-French four-factor and six-factor alphas.

We further explore this issue by first grouping stocks each month into deciles based on firm size; then, within each size decile, we sort stocks into quintiles based on AB_NR. In Panel

D of Table 5, we provide the hedge portfolio returns between the top and bottom quintiles by AB_NR within each size decile, for both equal-weighted and value-weighted portfolios. In this analysis, the high minus low AB_NR hedge portfolio return is significant for all but the largest size decile. This finding establishes that our main results are not confined to a limited set of small stocks in our sample but rather extend to all but the largest firms.

4.2.3. The intensity of a tug of war and the overnight versus daytime components of returns

In this section, we repeat our portfolio analysis from Panel A in Table 5 after decomposing future one-month returns into their overnight and daytime components. The results are provided in Panel E of Table 5. This analysis reveals that the positive predictive relation between AB_NR and future returns is driven by the overnight component of future monthly (close-to-close) returns, not the daytime component. In particular, the future *overnight* component of the mean monthly return on the AB_NR hedge portfolio is 4.65% (*t*-value = 7.16). In contrast, the future *daytime* component is opposite in sign and smaller in magnitude, at -3.69% (*t*-value = -8.38). This analysis corroborates similar evidence for the overnight and daytime components of stock returns documented in LPS, despite our use of a different sorting mechanism that is based on the monthly intensity of a daily tug of war.[17]

Overall, these results establish that the positive predictive information that emerges from a prolonged tug of war in month *t* is revealed through the trades of overnight investors in month

[17] Table A.3 of the Internet Appendix reproduces this analysis using value-weighted portfolios. The overnight and daytime components of value-weighted returns on the AB_NR hedge portfolio remain highly significant, though smaller in magnitude than the analogous equal-weighted evidence in Panel E of Table 5, and in LPS. Again, our evidence differs from LPS due to our use of a sorting mechanism based on the intensity of a daily tug of war.

t+1, not daytime traders. This outcome is consistent with our overcorrection conjecture, since overnight traders tend to be on the correct side of a prolonged tug of war.

4.2.4. Assessing economic significance

In this subsection, we assess the economic significance of our findings by comparing the return predictability of the abnormal intensity of a tug of war (AB_NR) with 17 other well-known asset pricing anomalies. We replicate these anomalies during our sample period (1993–2017) and compare their monthly hedge portfolio returns with that of AB_NR. Table A.4 of the Internet Appendix presents the average return (and the four-factor and six-factor alphas) for hedge portfolios that are long the top decile and short the bottom decile, based on each anomaly.

In column (1) of Table A.4, we first reproduce the results for AB_NR from Panel A in Table 5. While only nine of the 17 alternative strategies yield a significant alpha (based on equal-weighted six-factor alphas), our strategy provides one of the highest mean hedge portfolio returns with the highest statistical significance. Furthermore, only three of the alternative anomaly-based trading strategies (those based on ISSU, ACC, and NOA) yield a significant value-weighted six-factor alpha. These results establish that our analysis based on the intensity of a tug of war (AB_NR) is not only unique in providing a new firm attribute that has a low correlation with other anomalous firm attributes but also delivers hedge portfolio returns that are comparable to, and more statistically significant than, most other well-known anomalies.

4.3. Portfolio approach: Controlling for other firm characteristics

In this subsection, we examine the relation between AB_NR and other firm attributes and investigate whether the return predictability of AB_NR varies systematically with these attributes. First, we compare various characteristics across firms with high versus low AB_NR. Specifically, each month (*t*), we begin by sorting stocks into deciles based on AB_NR. For each

AB_NR decile, we then calculate the cross-sectional average values of these firm characteristics and compute the time series means of these monthly cross-sectional averages.

The results of this analysis are presented in Panel A of Table 6. These results are generally consistent with the correlations in Panel B of Table 3. In particular, there is no strong pattern for many firm characteristics across AB_NR deciles, including firm size (SIZE), return volatility (STDRET_M), the effective spread (ESPCT), analyst coverage (ANALYST), gross profitability (GPA), and asset growth (ATGTH). On the other hand, AB_NR is once again negatively associated with the cumulative close-to-close return in the same month *t* (RET). In addition, firms with a high AB_NR tend to be winning stocks in terms of past six-month returns (RET_6M) and to have high turnover (TURN_M). Stocks with high AB_NR also have lower book-to-market ratios (BM) and illiquidity (ILLIQ_M), although these differences tend to be driven by the bottom AB_NR decile. In Table A.5 of the Internet Appendix, we present a similar analysis based on several additional firm attributes, including alternative measures of illiquidity, the bid-ask spread, and volatility. While there is mixed evidence for a significant relation between AB_NR and alternative measures of illiquidity or the bid-ask spread, the subset of stocks in the top AB_NR decile tends to have significantly more volatile prices.[18]

[18] In untabulated analysis, we also characterize the subset of stocks that end up in the top AB_NR decile most frequently. We begin by counting the number of months in our sample that each firm ends up in the top AB_NR decile. We then normalize this count by the firm's age (in months). Each month (*t*), we then sort all firms that appear in the top decile based on AB_NR into terciles according to this frequency measure, and we compute the mean firm characteristics for each tercile by this frequency measure. We find that the subset of firms that end up in the top AB_NR decile most frequently tend to be subject to greater information asymmetry. Such firms are more likely to make daytime arbitrageurs mistakenly attribute a sequence of positive overnight returns to noise trading.

In addition, we apply a two-way sorting scheme to investigate whether the predictive relation between AB_NR and future returns varies when we account for the above firm attributes one at a time. Each month (*t*), we independently sort stocks into quintiles by AB_NR and into terciles by these firm attributes. All portfolios are held for one month (*t*+1).

We present the results in Panel B of Table 6. First, consider the two-way sort by AB_NR and the lagged monthly return (RET_{it}). The results show that firms with a high AB_NR outperform firms with a low AB_NR within each tercile based on the firm's lagged return. This result indicates that our findings are not driven by monthly return reversals. Next, consider analogous results for the two-way sorting schemes based on AB_NR and the firm's size, return volatility, illiquidity, effective spread, or analyst coverage, respectively. While the mean AB_NR hedge portfolio return is significant for all terciles based on each of these attributes, it is larger for firms with smaller size, greater volatility, higher illiquidity, higher effective spread, or lower analyst coverage. These firms are more opaque and susceptible to speculative trading by retail investors. As a result, it is more difficult for daytime arbitrageurs to disentangle possible information that arrives overnight from price pressure due to uninformed noise trading. Thus, in a prolonged tug of war, daytime investors are more likely to attribute a succession of positive overnight returns for these stocks to noise trading and to overcorrect, resulting in stronger predictive relations. This evidence also supports our conjecture that daytime investors tend to overcorrect overnight price pressure in a prolonged tug of war.

The remaining panels in Panel B of Table 6 provide similar analyses regarding AB_NR and future returns while controlling for other firm characteristics. Once again, the returns for hedge portfolios based on AB_NR are significant within all three terciles stratified by each firm attribute. This analysis establishes that firms with a high abnormal frequency of negative daytime reversals outperform those with a low abnormal frequency, even after controlling for other well-known predictors of stock returns.[19]

5. Testing additional implications of overcorrection

5.1. Placebo test: Daytime-to-overnight positive reversals

Thus far, we measure the intensity of a daily tug of war by focusing on the sequence of reversals that proceeds from a positive overnight return to a negative daytime reversal (NR). In this section, we consider the alternative sequence that proceeds from a negative daytime return to a positive overnight reversal. This sequence of daytime-to-overnight positive reversals (DOPR) is unrelated to our economic interpretation of negative reversals (NR) as a tug of war in which daytime arbitrageurs *respond* to positive overnight returns. A high frequency of daytime-to-overnight positive reversals (DOPR) should not reflect a persistent tug of war in which daytime arbitrageurs come to overcorrect positive overnight returns and, thus, it should not predict returns.

This observation suggests a placebo test based on the monthly frequency of trading days with daytime-to-overnight positive reversals (DOPR). We measure the abnormal frequency of such daytime-to-overnight positive reversals (AB_DOPR) following the same methodology used to obtain AB_NR. We then include both measures (AB_NR and AB_DOPR) in our regression

[19] We also repeat this analysis using *dependent* sorts in which we first sort stocks based on every firm characteristic and then, within each characteristic group, sort them based on AB_NR, as well as vice versa. The results of these dependent sorting schemes are presented in Table A.6 of the Internet Appendix and are robust with respect to the evidence in Panel B of Table 6. In addition, we conduct a battery of additional robustness tests that consistently yield further corroborating evidence in support of our main conjecture. These additional robustness tests are presented and discussed in Section A.3 and Tables A.7, A.8, and A.9 of the Internet Appendix.

model. If the tug of war emphasized in this paper is only characterized by days when arbitrageurs respond to positive overnight returns (AB_NR) and not vice versa, then we should expect a significant coefficient for AB_NR but not for AB_DOPR.

Panel A of Table 7 presents the summary statistics for DOPR and AB_DOPR, as well as their respective correlations with NR and AB_NR. Panel A indicates that DOPR and AB_DOPR have similar distributions to our analogous two measures of overnight-to-daytime negative reversals (NR and AB_NR) from Table 1. Moreover, the correlations across these four measures range from 0.59 to 0.72. This evidence is intuitive: since these alternative measures are similar by construction, a sequence of consecutive days that includes more than one positive overnight return followed by a negative daytime return should tend to yield similar measures for both AB_NR and AB_DOPR. On the other hand, these correlations are substantially below 1.00, which encourages us to proceed with the placebo test and examine whether variation in this alternative potential measure for a tug of war (DOPR) also predicts future returns.

We present the results of this placebo test in Panel B of Table 7. The coefficient of AB_NR remains positive and highly significant in every specification analyzed, while the coefficient of AB_DOPR is never significant and displays mixed signs across the columns. This simple placebo test provides powerful new evidence that only a persistent tug of war composed of sequences of positive overnight returns followed by negative daytime reversals (AB_NR) is associated with significant return predictability, and not vice versa (AB_DOPR). This evidence further supports our theory in which the tug of war involves daytime arbitrageurs *responding* to upward price pressure by overnight retail traders, rather than the other way around.

5.2. Negative daytime reversals, buying by retail traders, and short selling by arbitrageurs

In this subsection, we provide evidence of both greater buying by retail traders and short selling by arbitrageurs during months with a more intense tug of war.

5.2.1. The intensity of a tug of war and abnormal retail buying

Our main conjecture is based on the premise that the return predictability we show can be explained by a tendency for daytime arbitrageurs to overcorrect a prolonged sequence of positive overnight returns. This conjecture is, in part, based on the assertion that a significant amount of overnight trading is attributable to retail traders, and the role of overnight retail trading becomes more important during a persistent tug of war. This assertion is well established in the related literature.[20]

Ideally, we would like to examine the proportion of overnight trading that is attributable to retail investors, to further investigate our conjecture about the role of overnight retail trading during a more intense tug of war. Unfortunately, we do not have data that would allow us to specifically analyze the subset of total trading activity that is due to retail investors during the overnight non-trading period. Instead, we analyze data on retail trading volume available from the NYSE's Retail Execution Reports (ReTrac), which is limited to daily aggregated data on all purchases and sales by retail investors for a large cross section of NYSE stocks over the period 2004–2013.

For each firm (*i*) in month (*t*), we aggregate this daily retail trading activity across all days in the month and scale this measure by the firm's total monthly share volume from CRSP. We then follow the same procedure used to construct AB_NR and scale this measure by its own moving average over the previous 12 months, to obtain our monthly measure of abnormal retail

[20] See Aboody, Even-Tov, Lehavy, and Trueman (2018), Berkman, Koch, Tuttle, and Zhang (2012), and LPS.

trading activity. We also calculate the analogous measures for abnormal retail purchases and sales, separately. Finally, we regress each of these three monthly measures of retail trading activity (RETAIL) against AB_NR and the other control variables.

The results are presented in Panel A of Table 8. In column (1), the dependent variable is the abnormal proportion of total monthly trading activity by all retail investors. In columns (2) and (3), we analyze the intensity of monthly retail buying and selling separately. Columns (1) and (2) reveal a positive and significant coefficient for AB_NR, indicating heightened total retail trading and retail buying, respectively, during months with a more intense tug of war. In contrast, for retail selling in column (3), the coefficient of AB_NR is negative but insignificant. This evidence indicates that, during months with a more intense tug of war, there is a significant increase in retail trading activity that is driven by retail buying, as expected.

5.2.2. The intensity of a tug of war and abnormal short selling activity

If daytime investors tend to overcorrect the sequence of positive overnight returns during a more prolonged tug of war, then we should observe more short selling activity from daytime arbitrageurs. Although we cannot directly observe the actual selling activity by all daytime arbitrageurs, we have data on aggregate monthly short interest. Thus, we relate the abnormal frequency of negative daytime reversals (AB_NR) to short interest during the same month. Specifically, for each firm (*i*) in month (*t*), we follow the same procedure used to construct AB_NR, and scale total short interest by its own moving average over the previous 12 months to obtain our monthly measure of abnormal short selling activity (SHORT). We then regress this measure on AB_NR and various subsets of the other control variables.

The Fama-MacBeth regression results are presented in Panel B of Table 8. Across all four columns in Panel B, the coefficient of AB_NR is once again positive and significant. As predicted, these results indicate heightened short-selling activity during months with a more intense tug of war. For example, in column (4) this coefficient indicates that a one standard deviation increase in AB_NR is associated with a 6.7% (= 0.146 × 0.46) increase in monthly short selling activity, relative to its own moving average over the prior 12 months. This evidence is consistent with an explanation based on overcorrection by daytime arbitrageurs who display increased short selling activity during a more intense tug of war.

5.3. Negative daytime reversals and contemporaneous stock returns

If stocks are more prone to overcorrection by daytime investors during a more intense tug of war, then they are likely to have lower stock returns in the same month. Thus, we should observe a negative relation between AB_NR and contemporaneous monthly stock returns. We investigate this conjecture by regressing the contemporaneous return (RET_{it}) on AB_NR and the other control variables. We present the results in Table 9. For every specification analyzed, the coefficient of AB_NR is negative and significant. This finding further corroborates our conjecture that a more intense tug of war is associated with overcorrection of the recurring overnight price pressure during the same month.

5.4. Strategic intraday trading by arbitrageurs, the tug of war, and future returns

5.4.1. Strategic trading by daytime arbitrageurs and the intraday pattern of returns

To maximize their anticipated profits, daytime arbitrageurs who perceive that opening prices are too high should enter short positions early in the day. Furthermore, according to Bogousslavsky (2020), lending fees and overnight risk incentivize some daytime arbitrageurs to close their short positions before the end of the trading day. Thus, our theory, combined with that of Bogousslavsky (2020), suggests that, in an ongoing tug of war, daytime arbitrageurs should tend to aggressively short stocks with high opening prices early in the day. Late in the day, these arbitrageurs should tend to slow down their short selling activity, and some may even reverse their short positions. If more arbitrageurs act in this fashion for a given stock *i* during month *t*, then the subset of tug-of-war days (i.e., with a positive overnight return and a negative daytime reversal) should reveal an average negative intraday return pattern with a larger decline early in the day and a smaller decline or even a reversal late in the day.

We test this conjecture by decomposing the returns that occur throughout the trading day into 13 30-minute intervals between the open and the close (i.e., 9:30–16:00 ET). For each stock *i* during month *t*, we focus on the subset of tug-of-war days and calculate the average return for each of these 13 intraday periods. These tug-of-war days are selected to have a negative daytime return reversal by construction. Thus, we require a proper group of benchmark days to compare the average intraday patterns of these negative returns throughout the trading day. In this light, for each stock *i* during month *t*, we also consider the intraday return patterns for the alternative subset of benchmark days with negative returns during both the overnight and daytime trading sessions. While these benchmark days also have negative daytime returns, they do not reflect a tug of war between overnight and daytime traders.

Fig. 1 plots the resulting average intraday return patterns, which reveal that the subset of tug-of-war days (i.e., the blue bars) has a mean return of -0.74% for the first 30-minute interval. This large negative initial 30-minute return then becomes progressively smaller in magnitude across the other 30-minute intervals throughout most of the trading day, until it grows slightly larger near the close, with a mean return of -0.19% for the last 30-minute interval. In contrast, for the alternative subset of benchmark days (i.e., the green bars), the mean negative returns are smaller in magnitude over the first few 30-minute intervals and larger over the last few. For example, for benchmark days, the mean return over the first 30-minute interval is just -0.42%, while the last 30-minute interval has a mean return of -0.25%.

The differences across these pairs of mean 30-minute returns (the red bars in Fig. 1) highlight the systematic divergence in intraday return patterns across these two subsets of days. This evidence suggests that, for the subset of tug-of-war days, arbitrageurs as a group tend to exert more negative price pressure early in the day and less pressure late in the day, compared with benchmark days. The greater downward price pressure early in the day supports the view that arbitrageurs rush to short sell these stocks near the open when they are engaged in a tug of war with overnight traders. Furthermore, the lesser negative price pressure late in the day suggests that some arbitrageurs tend to slow down their short selling activity or even reverse their short positions just before the close, as argued by Bogousslavsky (2020).

5.4.2. Intraday return patterns and the predictive relation between AB_NR and future returns

In a prolonged tug of war when some daytime arbitrageurs tend to slow down their short selling activity or cover their short positions near the end of the trading day, the overcorrection of the recurring overnight price pressure should tend to dissipate. As a result, the predictive relation between AB_NR and future returns should be attenuated for the subset of stocks where the group of tug-of-war days reveals an intraday pattern of negative 30-minute returns that diminishes or reverses near the day’s close.

We investigate this implication of our theory combined with Bogousslavsky (2020) by creating two dummy variables that identify the group of stocks each month where the subset of tug-of-war days reveals a negative intraday return pattern that diminishes or reverses near the day’s close. First, for each firm i in month t, we focus on the subset of tug-of-war days with a positive overnight return and a negative daytime reversal. Then, for each firm i, we define a dummy variable, $I_{L30>F30}$, that equals one if the mean return for the last 30-minute interval across these tug-of-war days is larger (or smaller negative) than the mean return for the first 30-minute interval, and zero otherwise. Likewise, we assign a second dummy variable, $I_{L30>ALL}$, a value of one if the mean return for the last 30-minute interval is larger (or smaller negative) than the mean return across all earlier 30-minute intervals during the rest of the trading day, and zero otherwise.

We then include either dummy variable in our main regression specification, as well as its interaction with AB_NR. When either dummy is assigned a value of one, some daytime arbitrageurs in this tug of war appear to be acting in a way that results in less overcorrection, which should attenuate the return predictability in the following month. In this case, the coefficient of the interaction term between AB_NR and either dummy variable should be negative and significant.

The results of this analysis are presented in Table 10. For all specifications in this table, the coefficient of AB_NR remains positive and significant. In addition, as predicted by our theory combined with Bogousslavsky (2020), the coefficient of the interaction term between AB_NR and $I_{L30>F30}$ (or $I_{L30>ALL}$) is negative and significant. This evidence indicates that, when some arbitrageurs that are involved in a tug of war appear to slow down their short selling activity or cover their short positions late in the day, the relation between AB_NR and future returns is indeed significantly attenuated. Overall, this analysis of the intraday return patterns on tug-of-war days suggests that arbitrageurs trade in a manner consistent with our overcorrection hypothesis.[21]

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[21] Our overcorrection conjecture implies that daytime arbitrageurs appear to be on the losing side of a prolonged tug of war when evaluated in terms of future monthly returns. On the other hand, the subset of short-term arbitrageurs who pursue a strategy of repeatedly opening their short positions early in the morning and unwinding these positions

5.5. Negative daytime reversals, earnings announcements, and the earnings surprise

In this subsection, we examine whether the intensity of a daily tug of war conveys information about the firm's fundamental value, by conducting two tests. First, we investigate whether the abnormal intensity of a tug of war (AB_NR) tends to cluster during months with earnings announcements. We examine this issue by estimating a regression where the dependent variable is the abnormal frequency of negative reversals (AB_NR_{it}). We then include dummy variables that indicate whether an earnings announcement occurs in the same month as AB_NR_{it} (Month(0)) or in the subsequent month (Month(1)). The results are provided in Panel A of Table 11. In all four specifications tested, the coefficient of the first dummy (Month(0)) is positive and highly significant, while the second dummy (Month(1)) is insignificant. This evidence indicates that the intensity of a tug of war indeed tends to cluster around firm-specific information events that are likely to trigger an intensified tug of war.[22]

before the daily close appears to benefit from the tug of war, on average. Our analysis suggests that this group of short-term arbitrageurs is likely to represent a relatively small proportion of all daytime arbitrageurs. First, Fig. 1 reveals a steep price decline in the morning but a smaller price decline (rather than a reversal) near the daily close. Second, Panel B of Table 8 shows that short interest increases significantly during months with a more intense tug of war (i.e., a higher AB_NR). If most daytime arbitrageurs in an ongoing tug of war close their daily short positions before the close, then such behavior should lead to a positive reversal near the daily close in Fig. 1, and to a weaker relation between AB_NR and monthly short interest in Panel B of Table 8.

[22] We also repeat our main analysis from Table 4, after excluding firms with earnings announcements in month *t* or *t*+1. Our main results are robust, indicating that the predictive relation between the intensity of a tug of war (AB_NR) and future returns is not limited to months with earnings announcements. We present this evidence in Table A.10 of the Internet Appendix.

In our second test, we explore whether our proxy for the intensity of a tug of war in one month (AB_NR) predicts the firm's next earnings surprise. If daytime arbitrageurs tend to overcorrect positive news about the firm's future fundamentals during a more intense tug of war, then a higher value of AB_NR should be associated with a positive surprise at the next earnings release. We examine this issue by regressing the firm's next quarterly earnings surprise (SURPRISE) on AB_NR and the other controls, along with the most recent (lagged) earnings surprise. We measure the earnings surprise in two ways. First, we analyze the accounting-based standardized unexpected earnings surprise (SUE), following Bernard and Thomas (1990). Second, we use a market-based earnings surprise proxied by the three-day cumulative abnormal return (CAR) around the next earnings announcement.

We report the relevant results from this Fama-MacBeth regression analysis in Panel B of Table 11. The coefficient of our main variable of interest, AB_NR, is positive and significant in all four specifications tested. This evidence indicates that a higher abnormal frequency of negative reversals in one month is indeed associated with a more positive surprise at the firm's next earnings release. These results further corroborate our conjecture that daytime arbitrageurs tend to overcorrect the sequence of positive overnight returns in a more intense tug of war by failing to account for fundamental information about the firm's future earnings prospects.

5.6. Are negative reversals driven by negative news that arrives during the trading day?

In this subsection, we explore whether a higher frequency of positive overnight returns and negative daytime reversals captured by AB_NR simply reflects a tendency for daytime news to be more negative than overnight news, rather than overcorrection by daytime investors. On the other hand, if the average sentiment of daytime news is not more negative than overnight news on days with positive overnight returns and negative daytime reversals, then a high value of AB_NR is more likely to reflect overcorrection by daytime investors.

We obtain data on news flow from the Thomson Reuters NewsScope archive over the period 2003–2011; the archive includes firm-specific corporate news items from all public sources, along with a sentiment score for each item. For any given firm (*i*), we classify every news item as either negative, neutral, or positive based on the news sentiment score provided by Thomson Reuters. We assign numerical values of +1 to all positive news items, zero to all neutral items, and –1 to all negative items. Then, every day (*d*), we compute the average news sentiment score across all news items pertaining to each firm (*i*) that arrive either overnight or during the day.[23]

In Table 12, we report the means of the sentiment scores based on news that arrives either overnight or during the daytime for four subsets of firms each day: those with positive-negative reversals (NR), negative-positive reversals (PR), positive-positive days (PP), or negative-negative days (NN). Every day (*d*), we first compute the cross-sectional average of the overnight or daytime news sentiment scores across all firms (*i*) within each of the four subsets of firms listed above. For each of these four categories of firms, we then compute the time series mean of these daily cross-sectional average news sentiment measures across all days in the sample. We also provide the difference of means across sentiment measures between each of the first three categories and the fourth benchmark group of firms with overnight-daytime returns that are NN.

The top row of Table 12 indicates that, on days with positive overnight returns and negative daytime reversals (NR), the average firm has overnight news sentiment that is positive

[23] In Section A.4 of the Internet Appendix, we provide more details regarding the construction of our measures of average daytime or overnight news sentiment.

at +0.15, while daytime news sentiment is even more positive at +0.34. This evidence indicates that, on this subset of days, there are, on average, 15% (34%) more positive news items than negative news items that arrive during the overnight (daytime) period. It is noteworthy that, for this subset of days with negative daytime reversals, the average sentiment for daytime news is not just positive but even more positive than the average sentiment for overnight news.

This evidence suggests that a higher frequency of negative daytime reversals, embodied in a high value of AB_NR, is not due to a tendency for more negative news to arrive during the day versus the overnight period. Instead, this evidence is more consistent with an explanation based on overcorrection by daytime arbitrageurs during months with a more intense tug of war. This evidence also supports the conclusions of LPS, who suggest that daytime reversals are unlikely to be driven by differential news released overnight versus during the day.

6. Alternative potential explanations

6.1. Investor overreaction

In this subsection, we investigate whether investor overreaction could explain our results. As shown above, a high abnormal frequency of negative daytime reversals tends to be associated with positive news for the firm. Irrational investors may overreact to such positive news and bid up the firm’s price above what is warranted by fundamental value. However, one implication of such overreaction would be a positive contemporaneous relation between AB_NR and stock returns in the same month, rather than the negative relation we find in Table 9 above.

Another implication is that, if investor overreaction drives the predictive relation between AB_NR and future returns that we show, then such mispricing should eventually be corrected by a return reversal in the longer run. We examine this possibility by estimating a series of Fama-MacBeth regressions where the dependent variables are the future stock returns for each of the next 12 months (R_{it+a}, a = 1 – 12). The results are presented in Table 13. The coefficient of AB_NR is positive in 11 of the 12 specifications, and it is significant for regressions involving four of the next six months (it is not significant for month *t*+3 or month *t*+5). These results indicate that stocks with a higher abnormal frequency of negative daily reversals in month *t* continue to experience significantly higher returns for up to six months. On the other hand, this coefficient is insignificant for all months beyond month *t*+6, and there is no evidence of an eventual return reversal in the long run, beyond six months. This lack of a reversal is inconsistent with an explanation based on investor overreaction.[24]

6.2. Premium for risk due to disagreement between overnight and daytime clienteles

A higher frequency of positive overnight returns and negative daytime reversals reflects a greater divergence of beliefs between the two groups of traders who dominate the overnight and daytime trading periods in a tug of war. Thus, AB_NR also captures the level of disagreement between these opposing groups of investor clienteles. There is an extensive literature that argues that dispersion in investor beliefs should command a positive risk premium.[25] Hence, the predictive relation we show might be explained by heightened dispersion in beliefs across the groups of overnight traders and daytime investors, rather than our conjecture based on overcorrection by daytime arbitrageurs.

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[24] In unreported analysis, we extend this test for up to three years in the future and again find no evidence of a reversal.

[25] Among others, see Abel (1989), Anderson, Ghysels, and Juergens (2005, 2009), Banerjee (2011), Carlin, Longstaff, and Matoba (2014), David (2008), Doukas, Kim, and Pantzalis (2004), Qu, Starks, and Yan (2003), and Varian (1985).

However, our findings are unlikely to be explained by a risk premium associated with investor disagreement, for two reasons. First, this argument would imply a symmetric finding when we consider the abnormal frequency of either negative or positive daytime reversals. However, our finding is asymmetric, with only an abnormal frequency of positive overnight returns followed by negative daytime reversals predicting higher future returns.

Second, the disagreement argument also implies that a higher frequency of reversals that proceed either from positive overnight returns to negative daytime returns (AB_NR) or from negative daytime returns to positive overnight returns (AB_DOPR) should capture disagreement and predict returns. However, our placebo test in Table 7 shows that only AB_NR predicts future returns, which suggests that the disagreement premium channel cannot explain our findings.

6.3. Premium for arbitrageurs bearing 'noise trader risk' or 'overnight risk'

Another potential alternative explanation for our results is that stocks which display persistently high overnight returns in a prolonged tug of war are somehow more risky, so arbitrageurs require a premium for holding these stocks. There are two potential aspects of risk associated with stocks that display persistently high overnight returns in a prolonged tug of war.

First, the predictive relation we find may reflect a premium for arbitrageurs bearing "noise trader risk." As we show in Panel A of Table 8, a high frequency of positive overnight returns and negative daytime reversals is associated with heightened buying by retail investors. De Long, Shleifer, Summers, and Waldmann (1990) theorize that the beliefs of noise traders could deviate from fundamentals in the short run and become even more extreme in the near term before eventually reverting to fundamental value in the long run.[26] Since arbitrageurs are likely to be risk averse, have limited capital, and adhere to short investment horizons, the possibility of persistent and exacerbated price pressure caused by noise traders represents a risk that may deter arbitrageurs from trading. By making certain assets less attractive, this noise trader risk should initially drive prices down, as other market participants discount these stocks and demand a higher expected future return to compensate for this risk.

However, it is unlikely that the theory of De Long et al. (1990) explains our results. According to this argument, arbitrageurs should come to avoid trading against overnight noise traders during a more prolonged tug of war, since they are risk averse and have limited capital. But the persistence of these negative daily reversals suggests that arbitrageurs continue to trade against noise traders during months with a more intense tug of war. It is not clear how or why arbitrageurs would demand an additional risk premium for trading against noise traders, while they continue to trade against them during the daytime.

Second, according to Bogousslavsky (2020), arbitrageurs refrain from holding stocks overnight due to "overnight risk" stemming from heightened illiquidity and the risk of large price moves (see also Brock and Kleidon, 1992). Thus, the positive return predictability we show may represent compensation required by arbitrageurs for bearing this risk, rather than a tendency for arbitrageurs to overcorrect a sequence of positive overnight returns in a prolonged tug of war. In

[26] See also Banerjee and Green (2015), Black (1986), Bhushan, Brown, and Mello (1997), Bloomfield, O'Hara, and Saar (2009), Brown (1999), De Long, Shleifer, Summers, and Waldmann (1989), Dow and Gorton (1997, 2008), Gemmill and Thomas (2002), Kogan, Ross, Wang, and Westerfield (2006), Kyle (1985), Lee, Shleifer, and Thaler (1991), Mendel and Shleifer (2012), Palomino (1996), Pontiff (1996), Shleifer and Summers (1990), Sias, Starks, and Tinic (2001), Spiegel and Subrahmanyam (1992), Stambaugh (2014), and Trueman (1988).

this setting, the noise trader risk of De Long et al. (1990) and the overnight risk of Bogousslavsky (2020) are not mutually exclusive. One source of the risk of large price moves during the overnight period is the prevalence of noise traders, especially when liquidity is low.

However, our evidence in Table 10 is inconsistent with compensation for either noise trader risk or overnight risk. If stocks in a prolonged tug of war (i.e., with high AB_NR) are somehow more risky, especially during the overnight period, then daytime arbitrageurs should be more aggressive in covering their short positions before the daily close, as in Bogousslavsky (2020). In this case, our dummy variables ($I_{L30>F30}$ and $I_{L30>ALL}$) from Table 10 should capture subsets of stocks for which noise trader risk and overnight risk are heightened, so the associated risk premium should be greater, not smaller. Thus, according to this risk-based explanation, the coefficients of the interaction terms in Table 10 should have a positive sign rather than the negative sign we find. We conclude that arguments based on noise trader risk or overnight risk cannot explain our findings. Rather, the evidence in Table 10 is more consistent with our overcorrection hypothesis, which implies a weaker predictive relation based on AB_NR when daytime arbitrageurs slow down their short selling activity or cover their short positions late in the trading day, which should mitigate any potential overcorrection.

Finally, our placebo test in Table 7 using daytime-to-overnight positive reversals, AB_DOPR, (rather than overnight-to-daytime negative reversals, AB_NR) is also inconsistent with an explanation based on either noise trader risk or overnight risk. According to this alternative risk-based explanation, it should not matter whether the sequence of return reversals proceeds from positive overnight returns to negative daytime returns, or vice versa. However, we find that only AB_NR (and not AB_DOPR) predicts future returns in this placebo test.

7. Negative daytime reversals, market sentiment, and future stock returns

In this section, we examine the time-varying predictive power of AB_NR across periods of high versus low market sentiment, because the prior literature shows that sentiment plays an important role in affecting retail investor behavior and market mispricing (e.g., see Aboody et al., 2018; Baker and Wurgler, 2006; and Stambaugh, Yu, and Yuan, 2012). Ex ante, sentiment might affect the predictability of AB_NR in two opposing ways. On the one hand, high sentiment periods could be associated with more uninformed overnight trading. In this case, arbitrageurs who short these stocks during the day would be more likely to be on the correct side of trading in an ongoing tug of war. As a result, there should be less overcorrection, so the return predictability should be weaker. On the other hand, when sentiment is high, the tendency for daytime arbitrageurs to assume that a prolonged sequence of positive overnight returns is due to noise trading could make them even more likely to attribute this overnight price pressure to noise trading. In this case, we would expect even more overcorrection and consequently higher return predictability for AB_NR during periods of high sentiment.

Here we examine the impact of investor sentiment on hedge portfolio returns based on AB_NR, in the following time series regression model:

$$\text{Hedge Portfolio Return}_t = \alpha + \beta \text{ Risk Factors}_t + \gamma \text{ Sentiment}_{t-1} + \varepsilon_t, \qquad (1)$$

where the dependent variable is the return on a hedge portfolio that is long the decile of firms with a high value of AB_NR and short the decile with low AB_NR in month (t). We analyze two measures of investor sentiment (Sentiment), including the monthly index of Baker and Wurgler (2006) and a high sentiment indicator variable that is assigned a value of one for months when the Baker-Wurgler measure is above the median value for the entire sample period.[27]

In Table 14, we provide the coefficient of Sentiment (γ) for six different specifications of

[27] The sample period ends in 2015 due to data limitations on the sentiment index from Baker and Wurgler (2006).

Eq. (1). For every specification, the coefficient of Sentiment (γ) is positive and both statistically and economically significant. This evidence supports the argument that, when sentiment is high, daytime arbitrageurs have a greater tendency to assume that a prolonged sequence of positive overnight returns is due to noise trading. As a result, they are more likely to attribute this overnight price pressure to noise trading in an ongoing tug of war, resulting in greater overcorrection and a stronger predictive relation.

8. Summary and conclusions

Recent research shows a tendency for persistent patterns of positive overnight returns followed by negative daytime reversals in U.S. stocks, which suggests a recurring daily tug of war between opposing investor clienteles who trade overnight versus during the day. This body of work further suggests that uninformed noise traders dominate the overnight period, while arbitrageurs mainly operate during the day. We contribute to this literature by showing that stocks involved in a more intense tug of war, proxied by a higher monthly frequency of these negative daytime reversals, have significantly higher future returns.

This analysis is not only unique, providing a new firm attribute that has a low correlation with other anomalous firm attributes, but it also delivers future returns that are comparable to or exceed other well-known anomalies. This predictive relation remains when we consider various methods to adjust for risk, alternative sets of controls, different sample periods or listing exchanges, and alternative definitions of opening or closing prices. It also remains when we exclude months with earnings announcements, skip a month between portfolio formation and holding periods, and perform an out-of-sample test on NYSE stocks from 1926 to 1962.

We conjecture that this predictive relation is due to a tendency for daytime arbitrageurs to overcorrect the recurring positive overnight price pressure when there is a more intense tug of war. In a prolonged tug of war, daytime traders may come to discount the possibility that the ongoing sequence of positive overnight returns could signal the arrival of positive fundamental information. Instead, arbitrageurs may simply attribute this recurring overnight price pressure to uninformed noise traders and thus pull back too hard in correcting the perceived mispricing during the day. The resulting overcorrection by daytime arbitrageurs would lead to the predictive relation we show, as prices eventually adjust to firm fundamentals. Hence, in contrast to the prevailing literature, our findings imply that some component of overnight trading in a prolonged tug of war provides superior information relative to professional arbitrageurs.

Appendix 1. Variable descriptions and construction

Variable Name	Description & Construction
AB_NR_{it}	AB_NR_{it} is the abnormal frequency of *negative* daytime reversals for stock *i* in month *t*. It is defined as NR_{it} standardized by the average NR_{it} over the past 12 months. We require at least ten months of non-missing NR_{it} in the past 12 months to calculate its moving average.
AB_PR_{it}	The abnormal number of *positive* daytime reversals (AB_PR_{it}) is defined following the same procedure as AB_NR_{it}.
NR_{it}	NR_{it} is the ratio of the number of days with RET_CO>0 and RET_OC<0 (i.e., negative daytime reversals) to the total number of trading days for firm *i* in a given month *t*, where RET_CO is the overnight return from the previous day's closing price to the opening price on the current day, and RET_OC is the daytime return from the opening price to the closing price on the current day. We require at least 15 trading days in each month to calculate NR_{it}.
PR_{it}	PR_{it} is ratio of the number of days with RET_CO<0 and RET_OC>0 (i.e., positive daytime reversals) to the total number of trading days for firm *i* in a given month *t*.
AB_DOPR_{it}	AB_DOPR_{it} is the abnormal frequency of daytime-to-overnight positive reversals. We first define $DOPR_{it}$ as the ratio of the number of days with a negative daytime return followed by a positive overnight return (rather than a positive overnight return followed by a negative daytime return, as in the case of NR) to the total number of trading days for firm *i* in a given month *t*. AB_DOPR is then calculated as the ratio of DOPR to the average DOPR over the previous 12 months, following the same methodology used to obtain AB_NR.
$ATGTH_{it}$	Following Cooper, Gulen, and Schill (2008), we define annual asset growth for firm *i* in year *y*, as (Total $Assets_y$ − Total $Assets_{y-1}$) / (Total $Assets_{y-1}$), where year *y* is the fiscal year ending at least six months prior to month *t*.
BM_{it}	The firm's book-to-market ratio from the fiscal year ending at least six months prior to month *t*. We take the natural log.
$ESPCT_{it}$	ESPCT is the value-weighted percent effective spread. For each trade *k*, the percent effective spread is calculated as $2D_k(P_k–M_k)/M_k$, where D_k = +1 (–1) if the trade is a buy (sell) following Lee and Ready (1991), P_k is the price, and M_k is the midquote. The dollar value of shares traded is used as the weight applied to each trade.
GPA_{it}	The firm's annual gross profit from the fiscal year ending at least six months prior to month *t*, calculated as sales minus costs of goods sold scaled by total assets, following Novy-Marx (2013).
$I_{L30>F30}$ (or $I_{L30>ALL}$)	For each firm *i* in month *t*, $I_{L30>F30}$ is a dummy variable that takes a value of one if the mean return for the last 30-minute interval across the subset of tug-of-war days is larger than the mean return for the first 30-minute interval, and zero otherwise. The subset of tug-of-war days includes all days with a positive overnight return and a negative daytime reversal. $I_{L30>ALL}$ is an alternative dummy variable that takes a value of one if the mean return for the last 30-minute interval across the subset of tug-of-war days is larger than the mean return across all earlier 30-minute intervals during the rest of the trading day, and zero otherwise.
$ILLIQ\_M_{it}$	The firm's Amihud (2002) illiquidity measure: $\mathrm{ILLIQ} = \frac{1}{D_{it}} \sum_{t=1}^{Dit} \frac{\lvert R_{itd} \rvert}{VOLD_{itd}}$, where R_{itd} is the stock return for firm *i* on day *d* of month *t*, $VOLD_{itd}$ is the corresponding daily volume in dollars, and D_{it} is the number of days in month *t* for which data are available.
IO_{it}	The institutional ownership is defined as the number of shares held by all institutional investors in the quarter prior to month *t* divided by the number of shares outstanding.
RET_{id}	RET_{id} is the standard daily close-to-close return for firm *i* on day *d*.

Appendix 1, continued

Variable Name	Description & Construction
RET_CO_{id}	For each firm *i* on day *d*, RET_CO_{id} is the overnight (close-to-open) return component of the firm's close-to-close daily return. We follow Lou, Polk, and Skouras (2019), and impute this overnight return from the standard daily close-to-close return, RET_{id}, and the daytime open-to-close return, RET_OC_{id}, as $RET\_CO_{id} = \frac{1+RET_{id}}{1+RET\_OC_{id}} - 1$.
RET_OC_{id}	For each firm *i* on day *d*, RET_OC_{id} is the daytime (open-to-close) return, defined as the relative price change between market's opening and closing price on the same day *d*, $RET\_OC_{id} = \frac{P_{id}^{Close}}{P_{id}^{Open}} - 1$.
RET_{it}	RET_{it} is the standard monthly (close-to-close) return for firm *i* during month *t*, obtained from CRSP monthly files.
$RET\_CO\_M_{it}$	The compounded daily overnight (close-to-open) return for stock *i* in month *t*, obtained by cumulating all daily close-to-open returns throughout the month.
$RET\_OC\_M_{it}$	The compounded daily daytime (open-to-close) return for stock *i* during month *t*, obtained by cumulating all daily open-to-close returns throughout the month.
RET_6M_{it}	The firm's cumulative stock return over the past six months, from month *t*–6 to month *t*–1.
$RETAIL_{it}$	The proportion of total trading volume for stock *i* that is comprised of abnormal retail trading activity in month *t*, based on a sample of retail trades over the years, 2004–2013. First, we construct three measures that represent the proportion of total monthly trading volume comprised of (i) both retail purchases and sales, (ii) retail purchases, and (iii) retail sales. Next, we scale each of these three measures by their own mean values over the previous 12 months, to obtain our three measures of abnormal retail trading activity.
$SHORT_{it}$	The abnormal short interest in month *t*, calculated as the short interest scaled by its own mean value over the previous 12 months.
$SIZE_{it}$	The firm's market capitalization is defined as the total number of shares outstanding for firm *i* multiplied by the share price, on the last day of month *t*. We take the natural log of market capitalization.
$STDRET\_M_{it}$	The firm's volatility of daily stock returns during month *t*.
$SURPRISE_{it}$	The next quarterly earnings surprise following month *t* is measured in two ways. $SURPRISE_{1it}$ is the standardized unexpected earnings released by firm *i* in quarter *q* following month *t* based on the definition of Bernard and Thomas (1990). It is calculated as $\frac{EPS_{i,q}-EPS_{i,q-4}-\mu_{q-7,q}}{\sigma_{q-7,q}}$, where EPS is earnings per share, and $\mu_{q-7,q}$ and $\sigma_{q-7,q}$ are the mean and standard deviation of $EPS_{i,q} - EPS_{i,q-4}$ in the past eight quarters, respectively. $SURPRISE_{2it}$ is our alternative measure of earnings surprise, which is the cumulative abnormal return over the three days around the earnings announcement date in quarter *q*. It is calculated as CAR = $\frac{1}{3}\sum_{d=-1}^{+1}(RET_{i,d} - VWRETD_d)$, where $RET_{i,d}$ is the stock return for firm *i* on day d; $VWRETD_d$ is the value-weighted market return; and *d*=0 is the earnings announcement date.
$TURN\_M_{it}$	The firm's monthly share turnover is defined as trading volume (i.e., the number of shares traded) in month *t* divided by the total number of shares outstanding. We take the natural log of TURN_M.

References

Abdi, F., 2019. Cycles of declines and reversals following overnight market declines. Unpublished working paper. University of Massachusetts Amherst.

Abel, A., 1989. Asset prices under heterogeneous beliefs: Implications for the equity premium. Unpublished working paper. University of Pennsylvania.

Aboody, D., Even-Tov, O., Lehavy, R., Trueman, B., 2018. Overnight returns and firm-specific investor sentiment. Journal of Financial and Quantitative Analysis 53(2), 485-505.

Allen, F., Gale, D., 2005. From cash-in-the-market pricing to financial fragility. Journal of the European Economic Association 3(2/3), 535-546.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5(1), 31-56.

Anderson, E., Ghysels, E., Juergens, J., 2005. Do heterogeneous beliefs matter for asset pricing? Review of Financial Studies 18(3), 875-924.

Anderson, E., Ghysels, E., Juergens, J., 2009. The impact of risk and uncertainty on expected returns. Journal of Financial Economics 94(2), 233-263.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61(4), 1645-1680.

Banerjee, S., Green, B., 2015. Signal or noise? Uncertainty and learning about whether other traders are informed. Journal of Financial Economics 117(2), 398-423.

Banerjee, S., 2011. Learning from prices and the dispersion in beliefs. Review of Financial Studies 24(9), 3025-3068.

Barber, B., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21(2), 785-818.

Barclay, M., Hendershott, T., 2003. Price discovery and trading after hours. Review of Financial Studies 16(4), 1041-1073.

Berkman, H., Dimitrov, V., Jain, P., Koch, P., Tice, S., 2009. Sell on the news: Differences of opinion, short-sales constraints, and returns around earnings announcements. Journal of Financial Economics 92(3), 376-399.

Berkman, H., Koch, P., Tuttle, L., Zhang, Y., 2012. Paying attention: Overnight returns and the hidden cost of buying at the open. Journal of Financial and Quantitative Analysis 47(4), 715-741.

Bernard, V., Thomas, J., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305-340.

Bhushan, R., Brown, D., Mello, A., 1997. Do noise traders create their own space? Journal of Financial and Quantitative Analysis 32(1), 25-45.

Black, F., 1986. Noise. Journal of Finance 41(3), 529-543.

Bloomfield, R., O'Hara, M., Saar, G., 2009. How noise trading affects markets: An experimental analysis. Review of Financial Studies 22(6), 2275-2302.

Bogousslavsky, V., 2016. Infrequent rebalancing, return autocorrelation, and seasonality. Journal of Finance 71, 2967-3006.

Bogousslavsky, V., 2020. The cross-section of intraday and overnight returns. Journal of Financial Economics, Forthcoming.

Branch, B., Ma, A., 2012. Overnight return, the invisible hand behind intraday returns. Journal of Applied Finance 22(2), 90-100.

Brock, W., Kleidon, A., 1992. Periodic market closure and trading volume: A model of intraday bids and asks. Journal of Economic Dynamics and Control 16, 451-489.

Brown, G., 1999. Volatility, sentiment, and noise traders. Financial Analysts Journal 55(2), 82-90.

Brunnermeier, M., Pedersen, L., 2008. Market liquidity and funding liquidity. The Review of Financial Studies 22(6), 2201-2238.

Campbell, J., 2003. Consumption-based asset pricing. In: Constantinides, G., Harris, M., Stulz, R., (Eds.), Handbook of the Economics of Finance, Vol. 1, Elsevier, pp. 803-887.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52(1), 57-82.

Carlin, B., Longstaff, F., Matoba, K., 2014. Disagreement and asset prices. Journal of Financial Economics 114, 226-238.

Chabakauri, G., 2013. Dynamic equilibrium with two stocks, heterogeneous investors, and portfolio constraints. Review of Financial Studies 26(12), 3104-3141.

Chan, Y., Kogan, L., 2002. Catching up with the Joneses: Heterogeneous preferences and the dynamics of asset prices. Journal of Political Economy 110(6), 1255-1285.

Chen, J., Hong, H., Stein, J., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66(2-3), 171-205.

Christensen, P., Larsen, K., Munk, C., 2012. Equilibrium in securities markets with heterogeneous investors and unspanned income risk. Journal of Economic Theory 147(3), 1035-1063.

Cliff, M., Cooper, M., Gulen, H., 2008. Return differences between trading and non-trading hours: Like night and day. Unpublished working paper. University of Utah and Purdue University.

Cochrane, J., 2017. Macro-Finance. Review of Finance 21(3), 945-985.

Constantinides, G., Duffie, D., 1996. Asset pricing with heterogeneous consumers. Journal of Political Economy 104(2), 219-240.

Cooper, M., Gulen, H., Schill, M., 2008. Asset growth and the cross-section of stock returns, Journal of Finance 63(4), 1609-1651.

David, A., 2008. Heterogeneous beliefs, speculation, and the equity premium. The Journal of Finance 63(1), 41-83.

De Long, J., Shleifer, A., Summers, L., Waldmann, R., 1989. The size and incidence of the losses from noise trading. Journal of Finance 44(3), 681-696.

De Long, J., Shleifer, A., Summers, L., Waldmann, R., 1990. Noise trader risk in financial markets. Journal of Political Economy 98(4), 703-738.

Diether, K., Malloy, C., Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. The Journal of Finance 57(5), 2113-2141.

Doukas, J., Kim, C., Pantzalis, C., 2004. Divergent opinions and the performance of value stocks. Financial Analysts Journal 60(6), 55-64.

Dow, J., Gorton, G., 1997. Noise trading, delegated portfolio management, and economic welfare. Journal of Political Economy 105, 1024-1050.

Dow, J., Gorton, G., 2008. Noise traders. In: Durlauf, S., Blume, L., (Eds.) The New Palgrave: A Dictionary of Economics, Palgrave MacMillan, New York.

Edelen, R., Ince, O., Kadlec, G., 2016. Institutional investors and stock return anomalies. Journal Financial Economics 119, 472-488.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33(1), 3-56.

Fama, E., French, K., 2015. A five-factor asset pricing model. Journal of Financial Economics 116(1), 1-22.

Fama, E., French, K., 2018. Choosing factors. Journal of Financial Economics 128(2), 234-252.

Gârleanu, N., Panageas, S., 2015. Young, old, conservative, and bold: the implications of heterogeneity and finite lives for asset pricing. Journal of Political Economy 123(3), 670-685.

Gemmill, G., Thomas, D., 2002. Noise trading, costly arbitrage, and asset prices: Evidence from closed-end funds. Journal of Finance 57(6), 2571-2594.

Gromb, D., Vayanos, D., 2002. Equilibrium and welfare in markets with financially constrained arbitrageurs. Journal of Financial Economics 66(2-3), 361-407.

Gromb, D., Vayanos, D., 2010. Limits of arbitrage. Annual Review of Financial Economics 2(1), 251-275.

Grossman, S., Zhou, Z., 1996. Equilibrium analysis of portfolio insurance. Journal of Finance 51(4), 1379-1403.

Harrison, J., Kreps, D., 1978. Speculative investor behavior in a stock market with heterogeneous expectations. The Quarterly Journal of Economics 92(2), 323-336.

Hendershott, T., Livdan, D., Rösch, D., 2020. Asset pricing: A tale of night and day. Journal of Financial Economics 138(3), 635-662.

Heston, S., Korajczyk, R., Sadka, R., 2010. Intraday patterns in the cross-section of stock returns. Journal of Finance 65, 1369-1407.

Hirshleifer, D., Levi, Y., Lourie, B., Teoh, S., 2019. Decision fatigue and heuristic analyst forecasts. Journal of Financial Economics 133(1), 83-98.

Kahneman, D., Egan, P., 2011. Thinking, Fast and Slow, Vol. 1. Farrar, Straus and Giroux, New York, NY.

Kogan, L., Ross, S., Wang, J., Westerfield, M., 2006. The price impact and survival of irrational traders. Journal of Finance 61(1), 195-229.

Kyle, A., 1985. Continuous auctions and insider trading. Econometrica 53(6), 1315-1335.

Kyle, A., Xiong, W., 2001. Contagion as a wealth effect. Journal of Finance 56(4), 1401-1440.

Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. Journal of Finance, 46: 733-746.

Lee, C., Shleifer, A., Thaler, R., 1991. Investor sentiment and the closed-end fund puzzle. Journal of Finance 46(1), 75-109.

Lewellen, J., 2015. The cross-section of expected stock returns. Critical Finance Review 4, 1-44.

Lou, D., Polk, C., Skouras, S., 2019. A tug of war: Overnight versus intraday expected returns. Journal of Financial Economics 134(1), 192-213.

Mendel, B., Shleifer, A., 2012. Chasing noise. Journal of Financial Economics 104(2), 303-320.

Miller, E., 1977. Risk, uncertainty, and divergence of opinion. Journal of Finance 32(4), 1151-1168.

Miller, E., 1989. Explaining intra-day and overnight price behavior. Journal of Portfolio Management 15(4), 10-16.

Morris, S., Shin, H., Coordination risk and the price of debt. European Economic Review 48(1), 133-153.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108(1), 1-28.

Odean, T., 1999. Do investors trade too much? American Economic Review 89(5), 1279-1298.

Palomino, F., 1996. Noise trading in small markets. Journal of Finance 51(4), 1537-1550.

Pontiff, J., 1996. Costly arbitrage: Evidence from closed-end funds. The Quarterly Journal of Economics 111(4), 1135-1151.

Qu, S., Starks, L., Yan, H., 2003. Risk, dispersion of analyst forecasts and stock returns. Unpublished working Paper. University of Texas at Austin.

Santosh, S., 2016. The path of price discovery: Trade time vs. clock time. Unpublished working paper. University of Colorado at Boulder.

Shleifer, A., Summers, L., 1990. The noise trader approach to finance. Journal of Economic Perspectives 4(2), 19-33.

Shleifer, A., Vishny, R., 1997. The limits of arbitrage. The Journal of Finance 52(1), 35-55.

Sias, R., Starks, L., Tiniç, S., 2001. Is noise trader risk priced? Journal of Financial Research 24(3), 311-329.

Spiegel, M., Subrahmanyam, A., 1992. Informed speculation and hedging in a noncompetitive securities market. Review of Financial Studies 5(2), 307-329.

Stambaugh, R., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104(2), 288-302.

Stambaugh, R., 2014. Presidential address: Investment noise and trends. Journal of Finance 69(4), 1415-1453.

Stanovich, K., West, R., 2000. Advancing the rationality debate. Behavioral and Brain Sciences 23, 701-726.

Stein, J., 2009. Sophisticated investors and market efficiency. Journal of Finance 17(1), 165-206.

Trueman, B., 1988. A theory of noise trading in securities markets. Journal of Finance 43(1), 83-95.

Varian, H., 1985. Divergence of opinion in complete markets: A note. Journal of Finance 40(1), 309-317.

Table 1. Summary statistics for tug-of-war measures

This table presents summary statistics and correlations for our measures of the abnormal intensity of a daily tug of war (AB_NR and AB_PR). We also present analogous statistics for the level of the intensity tug of war (NR and PR). NR is the ratio of the number of days with RET_CO>0 and RET_OC<0 (i.e., negative daytime reversals) to the total number of trading days in a given month, where RET_CO is the overnight return from the previous day's closing price to the opening price on the current day, and RET_OC is the daytime return from the opening price to the closing price on the current day. AB_NR is the ratio of NR to the average NR over the past 12 months. PR is the ratio of the number of days with RET_CO<0 and RET_OC>0 (i.e., positive daytime reversals) to the total number of trading days in a given month. AB_PR is the ratio of PR to the average PR over the past 12 months. LeadAB_NR, LeadNR, LeadAB_PR, and LeadPR represent AB_NR, NR, AB_PR, and PR in month *t*+1, respectively.

These statistics are computed as time series averages of the monthly cross-sectional statistics. In Panel B, Spearman correlations appear above the diagonal and Pearson correlations below the diagonal. The sample period covers 1993–2017.

Panel A. Summary Statistics

	MEAN	STD	SKEW	KURT	MIN	P1	P5	P10	P25	MEDIAN	P75	P90	P95	P99	MAX
AB_NR	1.02	0.46	0.76	2.77	0.00	0.13	0.35	0.48	0.71	0.98	1.29	1.61	1.82	2.31	4.08
NR	0.25	0.11	0.38	0.17	0.00	0.03	0.09	0.12	0.18	0.25	0.32	0.40	0.44	0.53	0.70
AB_PR	1.03	0.48	0.70	1.36	0.00	0.11	0.33	0.46	0.69	0.98	1.31	1.64	1.87	2.38	3.79
PR	0.24	0.11	0.53	0.50	0.00	0.03	0.08	0.11	0.16	0.23	0.31	0.38	0.43	0.54	0.74

Panel B. Correlations

	AB_ NR	NR	AB_ PR	PR	Lead AB_ NR	Lead NR	Lead AB_ PR	Lead PR
AB_NR	1	0.89	-0.36	-0.32	0.09	0.08	-0.06	-0.06
NR	0.86	1	-0.32	-0.36	0.00	0.18	-0.02	-0.09
AB_PR	-0.36	-0.33	1	0.88	-0.07	-0.06	0.10	0.09
PR	-0.33	-0.38	0.85	1	-0.03	-0.09	0.01	0.20
LeadAB_NR	0.10	-0.01	-0.07	-0.03	1	0.89	-0.36	-0.32
LeadNR	0.08	0.20	-0.07	-0.10	0.86	1	-0.33	-0.36
LeadAB_PR	-0.07	-0.02	0.11	0.01	-0.36	-0.34	1	0.88
LeadPR	-0.06	-0.10	0.09	0.22	-0.33	-0.38	0.85	1

Table 2. Persistence of the abnormal frequency of daytime reversals

This table presents evidence regarding the persistence of AB_NR and AB_PR, using Fama-MacBeth regression where the dependent variable is the future value of the abnormal frequency of negative or positive daytime reversals (AB_NR_{it+a} or AB_PR_{it+a} where a = 1, 2, or 3 months ahead). For each forecast horizon, we estimate two versions of this model with or without the control variables in Table 4. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 monthly lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Panel A. Persistence of negative daytime reversals (AB_NR)

Dependent Variable:	(1) $\mathbf{AB\_NR_{it+1}}$	(2) $\mathbf{AB\_NR_{it+1}}$	(3) $\mathbf{AB\_NR_{it+2}}$	(4) $\mathbf{AB\_NR_{it+2}}$	(5) $\mathbf{AB\_NR_{it+3}}$	(6) $\mathbf{AB\_NR_{it+3}}$
AB_NR	0.118***	0.116***	0.075***	0.073***	0.058***	0.053***
	(16.20)	(17.49)	(10.86)	(12.63)	(13.48)	(14.14)
Controls	No	Yes	No	Yes	No	Yes
Adj. R^2	0.016	0.037	0.008	0.029	0.006	0.027
N	724,533	724,533	708,849	708,849	694,736	694,736

Panel B. Persistence of positive daytime reversals (AB_PR)

Dependent Variable:	(1) $\mathbf{AB\_PR_{it+1}}$	(2) $\mathbf{AB\_PR_{it+1}}$	(3) $\mathbf{AB\_PR_{it+2}}$	(4) $\mathbf{AB\_PR_{it+2}}$	(5) $\mathbf{AB\_PR_{it+3}}$	(6) $\mathbf{AB\_PR_{it+3}}$
AB_PR	0.123***	0.119***	0.077***	0.075***	0.056***	0.053***
	(17.72)	(19.64)	(12.81)	(14.77)	(12.79)	(13.77)
Controls	No	Yes	No	Yes	No	Yes
Adj. R^2	0.017	0.036	0.008	0.028	0.007	0.027
N	724,533	724,533	708,849	708,849	694,736	694,736

Table 3. Summary statistics and correlations for main variables

This table presents time-series averages of monthly cross-sectional summary statistics (Panel A) and monthly cross-sectional correlations (Panel B) for various stock characteristics. The sample contains common stocks listed on the NYSE, AMEX, and NASDAQ from May 1993 to December 2017. We exclude the stocks of financial firms and utility firms, as well as stocks with a month end price of less than $1. NR is the ratio of the number of days with RET_CO>0 and RET_OC<0 (i.e., negative daytime reversals) to the total number of trading days in a given month, where RET_CO is the overnight return from the previous day's closing price to the opening price on the current day, and RET_OC is the daytime return from the opening price to the closing price on the current day. AB_NR is the ratio of NR to the average NR over the past 12 months. PR is the ratio of the number of days with RET_CO<0 and RET_OC>0 (i.e., positive daytime reversals) to the total number of trading days in a given month. AB_PR is the ratio of PR to the average PR over the past 12 months. RET is the contemporaneous monthly return from CRSP in month *t*, when AB_NR is measured. RET_CO_M is the compounded daily overnight return during month *t*. RET_OC_M is the compounded daily daytime return during month *t*. SIZE is the market value of equity calculated as the number of shares outstanding times the month-end share price. BM is the ratio of book value to market value of equity. RET_6M is the cumulative (momentum) return from month *t*-6 to *t*-1. GPA is the gross profitability from Novy-Marx (2013). ATGTH is the asset growth from Cooper, Gulen, and Schill (2008). TURN_M is the turnover ratio measured as the number of shares traded divided by the number of shares outstanding in month *t*. STDRET_M is the volatility of daily returns during month *t*. ILLIQ_M is the Amihud (2002) measure of illiquidity in month *t*. IO is institutional ownership.

Panel A. Descriptive statistics

	MEAN	STD	MIN	P25	MEDIAN	P75	MAX
AB_NR	1.02	0.46	0.00	0.71	0.98	1.29	4.08
AB_PR	1.03	0.48	0.00	0.69	0.98	1.31	3.79
RET	0.01	0.16	-0.71	-0.07	0.00	0.08	1.94
RET_OC_M	0.01	0.18	-0.70	-0.07	0.01	0.08	2.72
RET_CO_M	0.01	0.14	-0.67	-0.04	0.00	0.05	2.05
SIZE	3.36	15.99	0.00	0.10	0.37	1.37	354.45
BM	0.71	1.15	0.00	0.28	0.49	0.84	33.28
RET_6M	0.09	0.45	-0.85	-0.15	0.03	0.23	6.91
GPA	0.35	0.33	-2.60	0.19	0.33	0.50	2.88
ATGTH	0.21	1.53	-0.81	-0.03	0.07	0.22	64.06
TURN_M	1.17	1.72	0.01	0.35	0.75	1.43	38.79
STDRET_M	0.03	0.02	0.00	0.02	0.03	0.04	0.35
ILLIQ_M	0.23	2.21	0.00	0.00	0.00	0.04	72.04
IO	0.51	0.29	0.00	0.27	0.56	0.76	1.00

Table 3, continued

Panel B. Correlations (Spearman above diagonal and Pearson below diagonal)

	AB_NR	AB_PR	RET	RETOC_M	RETCO_M	SIZE	BM	RET_6M	GPA	ATGTH	TURN_M	STDRET_M	ILLIQ_M	IO
AB_NR	1	-0.36	-0.16	-0.44	0.43	0.01	-0.03	0.05	0.00	-0.01	0.05	-0.01	-0.03	0.02
AB_PR	-0.36	1	0.17	0.44	-0.42	0.01	0.02	0.00	0.00	0.01	-0.03	-0.07	-0.01	-0.02
RET	-0.13	0.14	1	0.71	0.23	0.12	0.01	0.02	0.03	0.00	0.07	-0.03	-0.08	0.05
RETOC_M	-0.39	0.40	0.64	1	-0.39	0.04	0.05	0.02	0.06	-0.02	-0.07	-0.06	0.01	0.01
RETCO_M	0.36	-0.35	0.30	-0.43	1	0.06	-0.06	-0.01	-0.06	0.02	0.18	0.09	-0.09	0.02
SIZE	-0.01	-0.01	0.07	0.00	0.01	1	-0.29	0.19	0.00	0.16	0.47	-0.50	-0.95	0.65
BM	-0.02	0.03	0.02	0.06	-0.04	-0.26	1	0.00	-0.17	-0.18	-0.20	0.03	0.29	-0.08
RET_6M	0.05	0.00	0.01	0.00	-0.01	0.10	0.01	1	0.05	-0.05	0.07	-0.15	-0.18	0.07
GPA	0.00	0.00	0.02	0.05	-0.07	0.02	-0.06	0.02	1	0.02	-0.05	-0.09	0.00	0.06
ATGTH	-0.01	0.00	-0.02	-0.03	0.02	0.03	-0.07	-0.04	-0.06	1	0.13	-0.05	-0.16	0.11
TURN_M	0.04	-0.03	0.09	-0.08	0.17	0.41	-0.18	0.10	-0.04	0.06	1	0.09	-0.66	0.43
STDRET_M	0.01	-0.06	0.12	0.02	0.21	-0.42	0.02	-0.06	-0.10	0.02	0.14	1	0.47	-0.36
ILLIQ_M	-0.02	-0.01	-0.03	0.05	-0.05	-0.24	0.09	-0.06	0.02	-0.03	-0.21	0.19	1	-0.66
IO	0.01	-0.03	0.01	-0.03	-0.02	0.61	-0.07	0.00	0.08	-0.01	0.42	-0.33	-0.19	1

Table 4. Abnormal negative daytime reversals and future returns: Regression analysis

This table presents the Fama-MacBeth mean monthly coefficients for several regression specifications that include different subsets of the independent variables listed in Table 3. The dependent variable is the future stock return for firm *i* in month *t*+1 (RET_{it+1}). The key variables of interest are the monthly abnormal frequencies of negative and positive daytime reversals, respectively (AB_NR and AB_PR). The intercept for each specification is not shown below, for brevity. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Dependent Variable:	(1) $\mathbf{RET_{it+1}}$	(2) $\mathbf{RET_{it+1}}$	(3) $\mathbf{RET_{it+1}}$	(4) $\mathbf{RET_{it+1}}$	(5) $\mathbf{RET_{it+1}}$
AB_NR	**0.506*****	**0.431*****	**0.403*****	**0.339*****	
	(6.12)	**(6.69)**	**(6.42)**	**(6.18)**	
AB_PR	**-0.101**	**-0.049**	**-0.038**	**-0.093**	
	(-1.25)	**(-0.57)**	**(-0.46)**	**(-1.19)**	
RET_CO_M	-1.467***	-1.376***	-1.313***	-0.278	0.096
	(-2.68)	(-2.84)	(-2.75)	(-0.69)	(0.25)
RET_OC_M	-0.744	-1.207**	-1.392***	-1.102**	-1.492***
	(-1.54)	(-2.53)	(-2.95)	(-2.51)	(-3.67)
SIZE		-0.023	-0.018	-0.171***	-0.170***
		(-0.41)	(-0.32)	(-3.72)	(-3.62)
BM		0.229**	0.233**	0.197*	0.201*
		(1.97)	(1.99)	(1.89)	(1.92)
RET_6M		0.406	0.361	0.342	0.365
		(1.37)	(1.22)	(1.20)	(1.27)
GPA			0.588***	0.433**	0.440**
			(2.61)	(2.05)	(2.08)
ATGTH			-0.229***	-0.217***	-0.222***
			(-4.13)	(-3.80)	(-3.91)
TURN_M				0.222**	0.214**
				(2.08)	(1.99)
STDRET_M				-0.247***	-0.246***
				(-5.50)	(-5.53)
ILLIQ_M				0.225***	0.226***
				(3.83)	(3.85)
IO				-0.028	-0.002
				(-0.08)	(-0.00)
Adj. R^2	0.0109	0.0304	0.0354	0.0495	0.0487
N	749,430	749,430	749,430	749,430	749,430

Table 5. Abnormal negative daytime reversals and future returns: Portfolio analysis

Panel A of this table presents the equal-weighted results from one-way sorting analysis. Each month *t*, we sort all stocks into *deciles* based on the abnormal frequency of negative daytime reversals, AB_NR. We then assume that each *decile* portfolio is held during month *t*+1. In the top row of Panel A, we report the equal-weighted average raw returns for these decile portfolios in month *t*+1, RET_{it+1}, along with the average raw return for the high minus low hedge portfolio (H - L) that is long stocks with a high value of AB_NR and short stocks with a low AB_NR. In the remaining rows of Panel A, we report the analogous results based on the 4-factor (Carhart, 1997) and 6-factor (Fama and French, 2018) alphas for each portfolio.

Panel B reports the analogous value-weighted results from one-way sorting analysis, while Panel C presents the analogous value-weighted results when we exclude the largest one percent of firms each month (in terms of market capitalization, SIZE). Panel D provides both the equal-weighted and value-weighted results from two-way dependent sorting analysis based on firm size and AB_NR. Specifically, each month *t*, we first sort all stocks into deciles based on the firm's market capitalization. Then, within each size decile, we sort stocks into quintiles based on AB_NR, resulting in 50 portfolios in this 10 × 5 sorting scheme. For each size decile, we only present the results for the high minus low hedge portfolio (H - L) that is long stocks with a high value of AB_NR and short stocks with a low AB_NR.

In Panel E, we replicate the one-way portfolio analysis in Panel A after decomposing the future one-month return for each firm into its cumulative overnight and daytime components. The sample period covers 1993–2017. The *t*-statistics are based on Newey-West robust standard errors with 12 lags.
* indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Panel A. Equal-weighted portfolio returns

AB_NR	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**H - L**
Raw Return	0.58	0.64	0.85	0.85	0.85	0.98	0.96	1.16	1.30	1.50	0.92***
	(1.60)	(1.71)	(2.24)	(2.33)	(2.21)	(2.51)	(2.51)	(3.22)	(3.36)	(3.90)	(5.19)
FF4 α	-0.23	-0.24	-0.03	-0.03	-0.03	0.07	0.03	0.25	0.38	0.58	0.81***
	(-1.87)	(-2.22)	(-0.21)	(-0.32)	(-0.24)	(0.60)	(0.28)	(2.08)	(2.34)	(3.37)	(4.84)
FF6 α	-0.24	-0.23	0.02	0.05	0.06	0.15	0.10	0.29	0.46	0.62	0.85***
	(-1.92)	(-2.12)	(0.16)	(0.48)	(0.44)	(1.29)	(0.79)	(2.16)	(2.71)	(3.52)	(5.04)

Table 5, continued

Panel B. Value-weighted portfolio returns

AB_NR	Low	2	3	4	5	6	7	8	9	High	H - L
Raw Return	0.75	0.79	0.96	0.96	0.74	0.98	1.04	0.88	0.98	0.95	0.20
	(3.08)	(3.45)	(3.61)	(2.76)	(2.37)	(3.08)	(3.22)	(2.76)	(2.96)	(2.91)	(1.01)
FF4 α	0.00	-0.05	0.16	0.15	-0.09	0.06	0.23	-0.04	0.11	0.08	0.09
	(-0.01)	(-0.55)	(1.45)	(1.07)	(-0.90)	(0.47)	(2.02)	(-0.36)	(1.23)	(0.72)	(0.46)
FF6 α	-0.12	-0.13	0.11	0.18	-0.18	0.07	0.21	-0.06	0.16	-0.03	0.09
	(-1.05)	(-1.28)	(1.00)	(1.22)	(-1.69)	(0.56)	(1.82)	(-0.59)	(1.83)	(-0.23)	(0.52)

Panel C. Value-weighted portfolio returns, excluding the 1% of largest firms each month

AB_NR	Low	2	3	4	5	6	7	8	9	High	H - L
Raw Return	0.73	0.89	0.94	0.99	0.79	0.91	0.98	0.94	1.10	1.22	0.49***
	(2.70)	(3.23)	(3.18)	(3.44)	(2.47)	(2.88)	(3.03)	(3.12)	(3.23)	(3.72)	(3.03)
FF4 α	-0.12	0.04	0.08	0.09	-0.13	0.00	0.08	-0.01	0.11	0.29	0.41**
	(-1.07)	(0.43)	(1.07)	(0.99)	(-1.29)	(0.04)	(0.78)	(-0.12)	(1.26)	(2.47)	(2.48)
FF6 α	-0.27	0.01	0.10	0.12	-0.13	0.00	0.05	-0.06	0.09	0.12	0.39**
	(-2.78)	(0.08)	(1.16)	(1.18)	(-1.31)	(-0.01)	(0.48)	(-0.75)	(0.89)	(0.98)	(2.37)

Table 5, continued

Panel D. Hedge portfolio returns for the high minus low quintile portfolios based on AB_NR, within each decile portfolio based on firm size

		Hedge Portfolio Returns Based on AB_NR											
		Equal-Weighted						Value-Weighted					
		Raw Ret		FF4 α		FF6 α		Raw Ret		FF4 α		FF6 α	
		H-L	*t*	H-L	*t*	H-L	*t*	H-L	*t*	H-L	*t*	H-L	*t*
	L	0.68***	(3.17)	0.70***	(3.17)	0.88***	(3.90)	1.04***	(4.19)	1.00***	(3.86)	1.14***	(4.56)
	2	1.03***	(4.28)	0.93***	(3.51)	0.85***	(3.50)	1.00***	(3.89)	0.92***	(3.29)	0.87***	(3.30)
	3	1.13***	(3.83)	1.08***	(3.66)	1.14***	(3.65)	1.16***	(3.90)	1.09***	(3.68)	1.15***	(3.70)
	4	0.82***	(3.59)	0.66***	(2.93)	0.72***	(3.17)	0.81***	(3.63)	0.64***	(2.92)	0.71***	(3.19)
SIZE	5	0.74***	(4.81)	0.72***	(4.19)	0.83***	(4.69)	0.75***	(4.81)	0.73***	(4.14)	0.83***	(4.68)
	6	0.63***	(3.62)	0.58***	(3.27)	0.65***	(3.60)	0.61***	(3.56)	0.56***	(3.21)	0.62***	(3.51)
	7	0.48***	(2.72)	0.34**	(2.19)	0.37**	(2.51)	0.45**	(2.57)	0.30**	(1.99)	0.33**	(2.26)
	8	0.54***	(4.54)	0.49***	(3.79)	0.52***	(3.75)	0.51***	(4.21)	0.46***	(3.52)	0.51***	(3.56)
	9	0.49***	(2.97)	0.38***	(2.61)	0.34**	(2.15)	0.44**	(2.58)	0.32**	(2.07)	0.30*	(1.68)
	H	0.23*	(1.70)	0.13	(1.12)	0.11	(0.83)	0.15	(1.01)	0.07	(0.54)	0.12	(0.95)

Panel E. Decomposing future monthly returns into overnight and daytime components

AB_NR	**Low**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**High**	**H - L**
Overnight Returns											
Raw Return	-1.49	0.10	0.65	1.14	1.49	1.77	2.07	2.39	2.62	3.16	4.65***
	(-4.06)	(0.36)	(2.39)	(4.05)	(4.65)	(5.17)	(5.96)	(6.04)	(6.25)	(5.67)	(7.16)
FF4 α	-1.83	-0.26	0.29	0.81	1.16	1.43	1.73	2.06	2.31	3.03	4.87***
	(-5.42)	(-0.98)	(1.16)	(2.91)	(3.67)	(4.11)	(4.91)	(5.02)	(5.16)	(4.51)	(6.46)
FF6 α	-1.75	-0.23	0.34	0.86	1.21	1.49	1.73	2.10	2.34	2.97	4.72***
	(-5.48)	(-0.90)	(1.34)	(3.10)	(3.78)	(4.15)	(4.95)	(4.99)	(5.26)	(4.74)	(6.91)
Daytime Returns											
Raw Return	4.01	1.85	1.37	0.86	0.72	0.44	0.16	0.14	0.05	0.32	-3.69***
	(7.42)	(4.58)	(3.82)	(2.49)	(2.11)	(1.23)	(0.45)	(0.40)	(0.13)	(0.85)	(-8.38)
FF4 α	3.37	1.18	0.67	0.15	0.10	-0.27	-0.53	-0.57	-0.69	-0.44	-3.82***
	(6.55)	(3.31)	(2.29)	(0.58)	(0.28)	(-1.02)	(-1.95)	(-1.88)	(-2.46)	(-1.53)	(-8.29)
FF6 α	3.25	1.13	0.62	0.14	0.10	-0.28	-0.53	-0.64	-0.72	-0.48	-3.72***
	(6.53)	(3.22)	(2.14)	(0.54)	(0.28)	(-1.06)	(-2.00)	(-2.14)	(-2.53)	(-1.68)	(-8.22)

Table 6. Controlling for firm characteristics

Panel A presents the average firm attributes for stocks in the different AB_NR groups. RET is the contemporaneous monthly return from CRSP in month *t*, when AB_NR is measured. SIZE is the market value of equity calculated as the number of shares outstanding times the month-end share price. STDRET_M is the volatility of daily returns in month *t*. ILLIQ_M is the Amihud (2002) measure of illiquidity in month *t*. ESPCT is the value-weighted percent effective spread. For each trade *k*, the percent effective spread is calculated as $2D_k(P_k-M_k)/M_k$, where $D_k = +1$ (-1) if the trade is a buy (sell) following Lee and Ready (1991), P_k is the price, and M_k is the midquote. The dollar value of shares traded is used as the weight applied to each trade. ANALYST is analyst coverage. TURN_M is turnover measured as the number of shares traded divided by the number of shares outstanding in month *t*. RET_6M is the cumulative (momentum) return from month *t*-6 to *t*-1. BM is the ratio of book value to market value of equity. GPA is gross profitability from Novy-Marx (2013). ATGTH is asset growth from Cooper, Gulen, and Schill (2008).

Panel B presents results from two-way (5 × 3) sorting schemes, based on the abnormal frequency of negative daytime reversals, AB_NR, and the above firm attributes. In this analysis we independently sort the cross section of firms each month into quintiles by AB_NR and into terciles by each firm attribute. We then hold the resulting 15 portfolios in each 5 × 3 sorting scheme for one month. For each firm attribute, we only present the results for the high minus low hedge portfolio (H - L) that is long stocks with a high value of AB_NR and short stocks with a low AB_NR, within each tercile by the firm attribute. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-statistics are based on Newey-West robust standard errors with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Panel A. The attributes of stocks in different AB_NR deciles

AB_NR	**L**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**H**	**H_L**	**t-stat**
RET	4.41	3.73	2.78	2.28	1.64	0.92	0.36	-0.37	-1.32	-2.68	-7.10***	(-11.80)
SIZE	3.06	3.28	3.51	3.47	3.50	3.35	3.45	3.38	3.50	3.10	0.04	(0.28)
STDRET_M	3.28	3.29	3.28	3.29	3.29	3.29	3.28	3.29	3.29	3.35	0.06	(1.07)
ILLIQ_M	0.45	0.26	0.22	0.20	0.16	0.18	0.18	0.21	0.20	0.25	-0.20***	(-5.37)
ESPCT	1.39	1.21	1.15	1.12	1.11	1.11	1.11	1.12	1.16	1.34	-0.05*	(-1.65)
ANALYST	6.83	7.37	7.55	7.61	7.67	7.64	7.60	7.57	7.49	6.92	0.09	(0.91)
TURN_M	0.98	1.11	1.14	1.20	1.21	1.22	1.22	1.23	1.21	1.14	0.16***	(5.51)
RET_6M	0.06	0.07	0.07	0.08	0.08	0.09	0.10	0.10	0.11	0.13	0.07***	(5.18)
BM	0.81	0.73	0.71	0.70	0.69	0.68	0.68	0.67	0.68	0.73	-0.08***	(-3.44)
GPA	0.36	0.35	0.35	0.35	0.35	0.35	0.35	0.35	0.36	0.36	0.00	(-0.74)
ATGTH	0.18	0.23	0.23	0.22	0.23	0.21	0.23	0.21	0.21	0.17	-0.02	(-1.46)

Table 6, continued

Panel B. Two-way sorting analysis

Hedge Portfolio Returns Based on AB_NR																
		Raw Ret		FF4 α		FF6 α				Raw Ret		FF4 α		FF6 α	
Firm Char		H-L	*t*	H-L	*t*	H-L	*t*	Firm Char		H-L	*t*	H-L	*t*	H-L	*t*
	L	0.81***	(5.05)	0.70***	(3.88)	0.77***	(3.93)		L	0.90***	(6.60)	0.86***	(5.97)	0.83***	(5.70)
RET	2	0.72***	(5.85)	0.67***	(5.85)	0.67***	(5.55)	TURN_M	2	0.74***	(6.09)	0.68***	(5.51)	0.70***	(6.08)
	H	0.68***	(3.94)	0.60***	(3.87)	0.68***	(4.07)		H	0.62***	(3.60)	0.53***	(3.22)	0.65***	(3.56)
	L	0.97***	(5.72)	0.93***	(5.33)	0.98***	(5.63)		L	1.04***	(5.38)	1.01***	(4.81)	1.09***	(5.06)
SIZE	2	0.75***	(5.84)	0.64***	(4.78)	0.73***	(5.35)	RET_6M	2	0.63***	(5.24)	0.64***	(5.27)	0.63***	(5.38)
	H	0.43***	(3.93)	0.34***	(3.87)	0.35***	(3.75)		H	0.65***	(4.28)	0.52***	(3.78)	0.57***	(3.81)
	L	0.66***	(5.28)	0.57***	(5.22)	0.56***	(5.40)		L	0.96***	(5.43)	0.87***	(4.93)	0.91***	(5.34)
STDRET_M	2	0.69***	(4.81)	0.58***	(4.56)	0.62***	(5.01)	BM	2	0.83***	(6.13)	0.78***	(5.86)	0.80***	(6.41)
	H	1.00***	(4.90)	0.97***	(4.28)	1.07***	(4.58)		H	0.77***	(4.88)	0.71***	(4.48)	0.74***	(4.40)
	L	0.38***	(3.11)	0.27***	(2.67)	0.28***	(2.60)		L	0.71***	(3.60)	0.63***	(3.15)	0.73***	(3.61)
ILLIQ_M	2	0.74***	(4.79)	0.65***	(3.79)	0.77***	(4.39)	GPA	2	0.77***	(8.30)	0.68***	(7.29)	0.68***	(6.73)
	H	0.96***	(6.42)	0.94***	(6.24)	0.96***	(6.48)		H	0.84***	(5.80)	0.79***	(5.06)	0.82***	(5.37)
	L	0.49***	(4.14)	0.40***	(3.90)	0.38***	(3.52)		L	0.64***	(3.58)	0.59***	(2.85)	0.58***	(2.90)
ESPCT	2	0.70***	(4.71)	0.56***	(3.85)	0.63***	(4.41)	ATGTH	2	0.83***	(5.41)	0.79***	(4.61)	0.85***	(4.91)
	H	1.06***	(5.73)	1.02***	(5.26)	1.10***	(5.45)		H	0.77***	(6.32)	0.65***	(5.98)	0.72***	(6.19)
	L	0.90***	(4.64)	0.77***	(3.96)	0.81***	(4.01)								
ANALYST	2	0.90***	(5.68)	0.83***	(4.82)	0.84***	(5.13)								
	H	0.50***	(3.91)	0.42***	(3.49)	0.47***	(3.89)								

Table 7. Placebo test: Negative daytime returns followed by positive overnight reversals

In this table, we conduct a placebo test by analyzing an alternative monthly measure of a potential daily tug of war, based on daytime-to-overnight positive reversals (DOPR). Here we consider the frequency of days in a month with a negative daytime return followed by a positive overnight return, rather than a positive overnight return followed by a negative daytime return, as in the case of AB_NR. We also measure the abnormal frequency of daytime-to-overnight positive reversals (AB_DOPR) as the ratio of DOPR to the average DOPR over the previous 12 months, following the same methodology used to obtain AB_NR. Panel A presents the summary statistics for DOPR and AB_DOPR, as well as their respective correlations with NR and AB_NR. Panel B presents results from monthly Fama-MacBeth regressions where we extend the analysis in Table 4, by including AB_DOPR as an additional independent variable. The dependent variable is the future stock return for firm *i* in month *t+1* (RET_{it+1}). The intercept for each specification is not shown below, for brevity. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 monthly lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Panel A. Descriptive statistics for daytime-to-overnight positive reversals (DOPR and AB_DOPR)

	MEAN	STD	MIN	P25	MEDIAN	P75	MAX
DOPR	0.23	0.11	0.00	0.16	0.22	0.30	0.72
AB_ DOPR	1.02	0.47	0.00	0.70	0.98	1.30	4.06

	CORRELATION			
	SPEARMAN		PEARSON	
	NR	AB_NR	NR	AB_NR
DOPR	0.69	0.59	0.72	0.60
AB_ DOPR	0.59	0.66	0.60	0.69

Table 7, continued

Panel B. Predicting future stock returns with both AB_NR and AB_DOPR

Dependent Variable:	(1) $\mathbf{RET_{it+1}}$	(2) $\mathbf{RET_{it+1}}$	(3) $\mathbf{RET_{it+1}}$	(4) $\mathbf{RET_{it+1}}$
AB_NR	**0.546*** (6.53)**	**0.498*** (6.55)**	**0.468*** (6.31)**	**0.374*** (5.81)**
AB_ DOPR	**0.015 (0.23)**	**-0.026 (-0.46)**	**-0.031 (-0.53)**	**0.030 (0.54)**
RET_CO_M	-1.466*** (-2.65)	-1.429*** (-2.91)	-1.361*** (-2.83)	-0.334 (-0.79)
RET_OC_M	-0.723 (-1.47)	-1.199** (-2.44)	-1.382*** (-2.85)	-1.195*** (-2.66)
SIZE		-0.015 (-0.24)	-0.012 (-0.20)	-0.160*** (-3.34)
BM		0.223* (1.92)	0.227* (1.94)	0.186* (1.80)
RET_6M		0.407 (1.37)	0.362 (1.22)	0.347 (1.21)
GPA			0.587*** (2.60)	0.432** (2.03)
ATGTH			-0.226*** (-4.11)	-0.212*** (-3.75)
TURN_M				0.205* (1.93)
STDRET_M				-0.243*** (-5.01)
ILLIQ_M				0.296*** (3.19)
IO				0.023 (0.06)
Adj. R^2	0.012	0.034	0.040	0.055
N	711,067	711,067	711,067	711,067

Table 8. Abnormal negative daytime reversals, retail investor buying, and short selling

Panel A presents the results from Fama-MacBeth monthly regressions, which relate AB_NR to three different measures of abnormal retail investor trading activity ($RETAIL_{it}$), based on trades made by individual investors. Column (1) provides the results when the dependent variable is our measure of abnormal total retail investor trading activity for firm *i* in month *t*, based on both retail purchases and sales. Columns (2) and (3) provide the analogous results for abnormal retail purchases and sales, separately. The sample period for Panel A covers 2004–2013 due to the availability of retail trade data.

Panel B presents the Fama-MacBeth mean monthly coefficients from regressions that analyze abnormal short interest in firm *i* during month *t* ($SHORT_{it}$). Each model includes an intercept (not shown below). All variables are described in Appendix 1. The sample for Panel B covers the period 1993–2017. The *t*-statistics are based on Newey-West robust standard errors of the mean monthly regression coefficients, with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Panel A. Abnormal negative daytime reversals and retail investor trading

Dependent Variable:	(1) **$RETAIL_{it}$** (Purchases + Sales)	(2) **$RETAIL_{it}$** (Purchases)	(3) **$RETAIL_{it}$** (Sales)
AB_NR	**0.035****	**0.131*****	**-0.016**
	(2.09)	**(6.72)**	**(-0.70)**
RET_CO_M	0.204	-0.034	0.332*
	(1.31)	(-0.19)	(1.96)
RET_OC_M	0.147*	-0.402***	0.560***
	(1.90)	(-4.69)	(5.84)
SIZE	0.461	-0.209	-0.254
	(1.23)	(-0.40)	(-0.57)
BM	0.028**	0.012	0.042***
	(2.14)	(0.99)	(2.72)
RET_6M	-0.073***	-0.142***	-0.029
	(-3.32)	(-5.80)	(-0.98)
GPA	0.112***	0.106***	0.136***
	(3.62)	(2.67)	(4.06)
ATGTH	-0.017	-0.038***	-0.004
	(-1.62)	(-3.22)	(-0.33)
TURN_M	-6.008***	-7.489***	-7.867***
	(-4.42)	(-6.04)	(-4.81)
STDRET_M	6.350***	8.814***	5.196***
	(8.35)	(10.70)	(5.93)
ILLIQ_M	-58.075	-74.694	-60.090
	(-1.13)	(-1.46)	(-1.06)
IO	0.171***	0.223***	0.164***
	(8.55)	(6.17)	(7.70)
Adj. R^2	0.038	0.045	0.033
N	45,742	45,742	45,742

Table 8, continued

Panel B. Abnormal negative daytime reversals and short selling

Dependent Variable:	(1) **$SHORT_{it}$**	(2) **$SHORT_{it}$**	(3) **$SHORT_{it}$**	(4) **$SHORT_{it}$**
AB_NR	0.181***	0.153***	0.152***	0.146***
	(5.73)	(5.39)	(5.33)	(5.12)
RET_CO_M	1.786***	1.815***	1.819***	1.321***
	(6.40)	(6.57)	(6.52)	(6.21)
RET_OC_M	1.348***	1.354***	1.348***	1.169***
	(6.58)	(6.83)	(6.78)	(6.93)
SIZE		-0.067***	-0.067***	-0.058***
		(-5.71)	(-5.75)	(-3.87)
BM		-0.019	-0.017	0.018
		(-0.80)	(-0.76)	(0.95)
RET_6M		0.555***	0.556***	0.488***
		(10.47)	(10.61)	(10.83)
GPA			0.011	0.059
			(0.22)	(1.08)
ATGTH			0.008	0.000
			(0.87)	(-0.03)
TURN_M				0.162***
				(5.37)
STDRET_M				0.041*
				(1.78)
ILLIQ_M				-0.011
				(-0.60)
IO				-0.357***
				(-3.31)
Adj. R^2	0.014	0.035	0.035	0.052
N	584,357	584,357	584,357	584,357

Table 9. Abnormal negative daytime reversals and contemporaneous stock returns

This table presents the Fama-MacBeth mean monthly coefficients from estimating a regression where the dependent variable is the contemporaneous monthly return (RET_{it}). Each model includes an intercept (not shown below). All variables are described in Appendix 1. The sample covers the period 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Dependent Variable:	(1) **RET_{it}**	(2) **RET_{it}**	(3) **RET_{it}**	(4) **RET_{it}**
AB_NR	**-4.781*** **	**-4.808*** **	**-4.798*** **	**-4.760*** **
	(-11.53)	**(-12.27)**	**(-12.25)**	**(-12.23)**
RET_CO_M	-0.626	-0.646	-0.606	0.134
	(-1.24)	(-1.46)	(-1.39)	(0.36)
RET_OC_M	-1.447***	-1.812***	-1.976***	-1.803***
	(-3.14)	(-3.92)	(-4.28)	(-4.18)
SIZE		-0.051	-0.045	-0.183***
		(-0.85)	(-0.77)	(-3.60)
BM		0.225*	0.228*	0.193*
		(1.93)	(1.93)	(1.85)
RET_6M		0.621**	0.572**	0.573**
		(2.15)	(1.98)	(2.03)
GPA			0.595***	0.455**
			(2.60)	(2.12)
ATGTH			-0.256***	-0.242***
			(-4.40)	(-4.05)
TURN_M				0.200*
				(1.88)
STDRET_M				-0.186***
				(-4.29)
ILLIQ_M				0.274***
				(4.15)
IO				0.221
				(0.61)
Adj. R^2	0.030	0.050	0.055	0.069
N	739,163	739,163	739,163	739,163

Table 10. AB_NR and future stock returns, conditional on intraday return patterns

This table presents results from Fama-MacBeth regressions that relate our proxy for the intensity of a tug of war (AB_NR) to future stock returns, conditional on the nature of the firm's average intraday return pattern for the subset of tug-of-war days during the month. First, for each firm *i* in month *t*, we focus on the subset of tug-of-war days with a positive overnight return and a negative daytime reversal. We then assign the dummy variable, $I_{L30>F30}$, a value of one if the mean return for the last 30-minute interval across the subset of tug-of-war days is larger (or smaller negative) than the mean return for the first 30-minute interval, and zero otherwise. We also define an alternative dummy variable, $I_{L30>ALL}$, that takes a value of one if the mean return for the last 30-minute interval across these tug-of-war days is larger (or smaller negative) than the mean return across all earlier 30-minute intervals during the rest of the trading day, and zero otherwise. We then include either dummy variable in our main regression specification, along with its interaction with AB_NR. The dependent variable is the future stock return for firm *i* in month *t*+1 (RET_{it+1}). The intercept and coefficients for the control variables are not shown below, for brevity. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Dependent Variable:	(1) **RET_{it+1}**	(2) **RET_{it+1}**	(3) **RET_{it+1}**	(4) **RET_{it+1}**
AB_NR	0.710***	0.458***	0.668***	0.430***
	(5.68)	(5.27)	(6.86)	(6.18)
$I_{L30>F30}$	0.102	0.126		
	(0.73)	(1.09)		
AB_ NR × $I_{L30>F30}$	**-0.218****	**-0.186***		
	(-2.09)	**(-1.94)**		
$I_{L30>ALL}$			0.029	0.012
			(0.29)	(0.12)
AB_ NR × $I_{L30>ALL}$			**-0.216****	**-0.193****
			(-2.44)	**(-2.23)**
Controls	No	Yes	No	Yes
Adj. R^2	0.002	0.049	0.001	0.049
N	737,851	737,851	737,851	737,851

Table 11. Abnormal negative daytime reversals and earnings announcements

In Panel A, we use Fama-MacBeth regression analysis to explore whether our measure for the intensity of a tug of war (AB_NR) tends to cluster in the month of or the month before earnings announcements. The dependent variable is the abnormal frequency of negative daytime reversals (AB_NR_{it}). We then include dummy variables that indicate whether an earnings announcement occurs in the same month as AB_NR_{it} or the month after. In particular, the dummy variable Month(0) takes a value of one if an earnings announcement occurs in month *t* (i.e., the same month that AB_NR_{it} is measured), while Month(1) takes a value of one if an earnings announcement occurs in month *t*+1 (i.e., one month after AB_NR_{it} is measured).

Panel B presents the results from Fama-MacBeth regressions that relate the abnormal frequency of negative daytime reversals to the firm's next earnings surprise. We measure the next earnings surprise in two ways, including an accounting-based measure and a market-based measure. $SURPRISE_{1it}$ is the accounting-based standardized unexpected earnings (SUE) associated with earnings released by firm *i* in the next quarter (*q*) following month *t*, based on the definition of Bernard and Thomas (1990). It is calculated as $\frac{EPS_{i,q} - EPS_{i,q-4} - \mu_{q-7,q}}{\sigma_{q-7,q}}$, where EPS is earnings per share; $\mu_{q-7,q}$ and $\sigma_{q-7,q}$ are the mean and standard deviation of $(EPS_{i,q} - EPS_{i,q-4})$ across the past eight quarters, respectively. $SURPRISE_{2it}$ is our market-based measure of the earnings surprise, defined as the cumulative abnormal return over the three days around the next earnings announcement in quarter *q*: CAR = $\frac{1}{3}\sum_{d=-1}^{+1}(RET_{i,d} - VWRETD_{d})$, where $RET_{i,d}$ is the stock return for firm *i* on day d; $VWRETD_d$ is the value-weighted market return; and *d*=0 is the earnings announcement date. We include the most recent (lagged) quarterly earnings surprise as an independent variable in columns (2) and (4), along with the standard control variables in Table 4. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Table 11, continued

Panel A. Clustering of abnormal negative daytime reversals during months with an earnings announcement

Dependent Variable:	(1) AB_NR_{it}	(2) AB_NR_{it}	(3) AB_NR_{it}	(4) AB_NR_{it}
Month(0)	**0.013*** (5.57)**	**0.013*** (6.43)**	**0.013*** (4.75)**	**0.012*** (5.08)**
Month(1)			0.001 (0.35)	-0.001 (-0.64)
Controls	No	Yes	No	Yes
Adj. R^2	0.005	0.026	0.005	0.026
N	724,533	724,533	724,533	724,533

Panel B. Abnormal negative daytime reversals and the next earnings surprise

Dependent Variable:	(1) $SURPRISE_{1it}$	(2) $SURPRISE_{1it}$	(3) $SURPRISE_{2it}$	(4) $SURPRISE_{2it}$
AB_NR	**0.031*** (6.06)**	**0.009* (1.81)**	**0.043*** (3.91)**	**0.043*** (3.89)**
Lagged SURPRISE		0.319*** (43.02)		0.012*** (3.19)
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.046	0.139	0.011	0.012
N	611,087	611,087	611,087	611,087

Table 12. Average sentiment of news that arrives overnight or during the daytime, for days with positive overnight returns and negative daytime reversals, versus other days

In this table we report the time series means of average daily measures of sentiment based on news items that arrive either overnight or during the daytime, for four subsets of firms each day that have respective (overnight, daytime) returns that are (positive, negative), (negative, positive), (positive, positive), or (negative, negative). The news data are taken from the Thomson Reuters Newsscope archive over the period 2003–2011. For any given firm *i*, we classify every news item as either negative, neutral, or positive, based on the news sentiment score provided by Thomson Reuters. We assign numerical values of +1 to all positive news items, zero to all neutral items, and –1 to all negative items. Then, every day (*d*), we compute the average news sentiment score across all news items pertaining to each firm *i* that arrive either overnight or during the day. Next, for each day *d*, we calculate the cross-sectional average of the overnight or daytime news sentiment scores across all firms *i* within each of the four subsets of firms with the different categories of (overnight, daytime) returns listed above. Finally, for each of these four categories of (overnight, daytime) returns, we compute the time series mean of these daily cross sectional average news sentiment measures across all days in the sample period. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the time series mean daily news scores, with 12 daily lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

	Average News Sentiment		**Difference Between Each Category of Days and the (Negative, Negative) Group**	
Category	**Overnight**	**Day Time**	**Overnight**	**Day Time**
(Positive, Negative)	0.15***	0.34***	0.07***	0.29***
(Negative, Positive)	0.10***	0.14***	0.04***	0.09***
(Positive, Positive)	0.19***	0.39***	0.12***	0.34***
(Negative, Negative)	0.07***	0.06***		

Table 13. Abnormal negative daytime reversals and long term future returns

This table presents the Fama-MacBeth mean monthly coefficients for AB_NR, from regression analysis that replaces the dependent variable from the model analyzed in Table 4, the one-month-ahead stock return (RET_{it+1}), with a series of future monthly returns that span each of the next 12 months. All variables are described in Appendix 1. The sample period covers 1993–2017. The *t*-ratios (in parentheses) are based on Newey-West robust standard errors of the mean monthly coefficients, with 12 monthly lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Dependent Variable:	(1) **RET_{it+1}**	(2) **RET_{it+2}**	(3) **RET_{it+3}**	(4) **RET_{it+4}**	(5) **RET_{it+5}**	(6) **RET_{it+6}**
AB_NR	**0.353*****	**0.233*****	0.003	**0.141****	0.100	**0.160****
	(6.11)	**(4.32)**	(0.05)	**(2.15)**	(1.12)	**(2.06)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.049	0.045	0.043	0.042	0.040	0.040
N	749,430	744,994	740,506	735,944	731,305	726,624

Dependent Variable:	(7) **RET_{it+7}**	(8) **RET_{it+8}**	(9) **RET_{it+9}**	(10) **RET_{it+10}**	(11) **RET_{it+11}**	(12) **RET_{it+12}**
AB_NR	0.005	0.108	0.071	0.023	-0.042	0.033
	(0.07)	(1.24)	(0.89)	(0.28)	(-0.60)	(0.56)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.038	0.037	0.036	0.036	0.036	0.035
N	720,038	713,406	706,758	700,104	693,426	686,764

Table 14. Negative daytime reversals, future stock returns, and investor sentiment

This table examines the association between investor sentiment and the magnitude of the monthly hedge portfolio returns based on the abnormal frequency of negative daytime reversals (AB_NR). In each month *t*, we first sort stocks into deciles based on AB_NR. We next calculate monthly returns to the hedge portfolio that is long stocks with a high value of AB_NR and short stocks with a low AB_NR. We then estimate the time series regression model specified in Eq. (1), where we regress these hedge portfolio returns on the various risk factors in the Fama-French four-factor or six-factor model, along with the lagged value of the monthly sentiment measure from Baker and Wurgler (2006). In addition to this continuous monthly sentiment measure, we also analyze a high sentiment dummy variable that takes a value of one for the subset of months in which the continuous sentiment measure is above the median value taken over the entire sample period covering 1993–2015. Note that this sample ends in 2015 rather than 2017 due to the availability of Baker and Wurgler's sentiment measure. For brevity, we only present the coefficient of the continuous sentiment measure and the high sentiment dummy variable, respectively, for each model analyzed. The *t*-statistics are based on Newey-West robust standard errors with 12 lags. * indicates significance at the 0.10 level; ** at the 0.05 level; and *** at the 0.01 level.

Model	Continuous Sentiment Measure		High Sentiment Dummy	
	Coefficient	t-value	Coefficient	t-value
No risk factors	0.47*	(1.73)	0.64**	(2.22)
Fama-French 4-Factor	0.77***	(3.28)	0.88***	(2.79)
Fama-French 6-Factor	0.82***	(3.29)	0.91***	(2.83)

Figure 1. Intra-day return patterns on tug-of-war days versus benchmark days with a negative return during both the overnight and trading day periods

The blue bars in this figure present the average 30-minute returns for each of the 13 30-minute intervals during the trading day, from 9:30 to 16:00 EST, for the subset of tug-of-war days with a positive overnight return followed by a negative daytime reversal. These average returns are obtained as follows. First, for each trading day (*d*), we focus on the subset of stocks that have a positive overnight return and a negative trading day reversal. Then, we calculate the time series average of the cross-sectional daily mean returns for each of these 13 intraday periods. The green bars provide the analogous results for the alternative group of benchmark days with negative returns during both the overnight and trading day periods. Finally, the red bars plot the difference between the average returns across these two groups of tug-of-war days versus benchmark days, for each 30-minute interval.