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Shorting flows, public disclosure, and market efficiency

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ABSTRACT

Shorting flows remain a significant predictor of negative future stock returns during 2010–2015, when daily short-sale volume data are published in real time. This predictability decays slowly and lasts for a year. Long-term shorting flows are more informative than short-term shorting flows. Indeed, abnormal short-term shorting flows do not predict future returns or anticipate bad news. We find that short sellers exploit prominent anomalies. A comparison with the Regulation SHO data indicates that the predictability is much shorter-term during 2005–2007. Short sellers appear to have shifted from trading on short-term private information to trading on long-term public information that is gradually incorporated into prices.

1. Introduction

The informational role of short sellers in financial markets has been the subject of extensive academic research for several decades. Prior studies using monthly short interest data find mixed evidence on whether short sellers are informed about future returns (e.g., Figlewski, 1981; Brent et al., 1990; Desai et al., 2002; Asquith et al., 2005). In contrast, more recent studies examining daily shorting flows find uniformly strong evidence that heavily shorted stocks underperform lightly shorted stocks (e.g., Boehmer et al., 2008; Diether et al., 2009). Both Boehmer et al. (2008) and Diether et al. (2009) emphasize that their results do not contradict the semi-strong form of market efficiency because investors do not have access to their data.[1]

In this paper we reexamine the predictive ability of shorting flows during 2010–2015, a period in which the daily short-sale volume data are publicly disclosed in real time. Motivated by concerns about the role of short sellers in the market crash of 2008–2009, the Securities and Exchange Commission (SEC) requested that the Financial Industry Regulatory Authority, Inc. (FINRA) publish stock-level aggregate short-sale volume on a daily basis.[2] This new data set provides a unique opportunity to examine the informativeness of short sales and the extent to which the market is informationally efficient. In particular, if the market is efficient in processing and impounding public

[1] Boehmer et al. (2008) use a proprietary data set from the NYSE, and Diether et al. (2009) use the Regulation SHO data, which are publicly available but not in real time.

[2] FINRA typically publishes the data on the same day of trading (after the end of regular trading hours) and, in rare instances, during the next business day.

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shorting information, we would expect the predictive ability of daily shorting flows to disappear beyond a holding period of one day. The availability of this new data set also allows us to shed light on the ongoing debate about the benefits and costs of real-time disclosure of short selling activities.

Our results indicate that shorting flows continue to be a significant predictor of negative future stock returns during 2010–2015. We follow the methodology of Boehmer et al. (2008) and form quintile portfolios each day based on prior five days of shorting activities. We skip one day and hold these portfolios for 20 days. We find that heavily shorted stocks underperform lightly shorted stocks by an annualized risk-adjusted return of 12.6% (t-statistic = 6.00) for equal-weighted portfolios and by 6.0% (t-statistic = 4.03) for value-weighted portfolios. These results suggest that short sellers are well informed during our sample period and that the market is slow to incorporate public shorting information into prices.

We interpret the predictive ability of shorting flows as suggesting that short sellers contribute to market efficiency by bringing prices closer to the fundamentals. However, this predictability could also arise as a result of destabilizing shorting. In particular, public disclosure of short-sale data may serve as a coordination mechanism for manipulative shorting attacks, which would push prices below fundamental values (Brunnermeier and Oehmke, 2014). Another form of destabilizing shorting is crowding (Stein, 2009). Given the well-documented results of Boehmer et al. (2008) and Diether et al. (2009), it is natural to expect that public disclosure of high short-sale volume on a stock will attract more short sellers. Such trading resembles positive-feedback trading and, more importantly, has no anchor in fundamentals. Therefore, if too many investors act on this information, price may overshoot. In both manipulative shorting and crowded shorting, price will decline in the short run, leading to short-term predictability; and will reverse to the fundamental value in the long run, causing long-term reversal. By contrast, if the predictive ability of shorting flows is due to informed shorting, then any price impact will be permanent, i.e., there is no reversal.

To differentiate between informed shorting and destabilizing shorting, we examine the long-run performance of shorting portfolios up to a year. We find no evidence of price reversal. On the contrary, we find significant evidence of return continuation. Heavily shorted stocks continue to underperform lightly shorted stocks during the month, quarter, and year after the initial holding period. The absence of long-run reversal is consistent with informed shorting and inconsistent with destabilizing shorting.

Previous studies of daily shorting flows focus exclusively on short-term predictability and conclude that short sellers primarily trade on short-term information. Our finding that the predictive ability of shorting flows decays slowly and persists for a year, however, raises the possibility that short sellers trade on long-term information that is gradually incorporated into prices. To provide more evidence on this possibility, we compare the informativeness of long-term versus short-term shorting flows. If short sellers specialize in trading on short-term information, we would expect short-term shorting flows to exhibit stronger predictive power for future stock returns than long-term shorting flows. We measure long-term shorting flows over the month or quarter prior to the past week and find that stocks with the highest long-term shorting flows significantly underperform stocks with the lowest long-term shorting flows. Moreover, the magnitude of this underperformance is larger than that based on short-term shorting flows, suggesting that long-term shorting flows are more informative than short-term shorting flows.

We continue our investigation into whether short sellers trade on short- versus long-term information by examining whether abnormal shorting flows predict future returns. We define abnormal shorting flows as the difference between short-term shorting flows (average shorting over the past week) and long-term shorting flows (average shorting over the month or quarter prior to the past week). Because of the significant holding cost associated with short selling, we would expect short sellers who possess short-term information to place their trades just prior to the release of such information instead of holding short positions for months or years. As a result, high abnormal shorting flows, i.e., a significant increase in shorting flows, should predict low future returns. However, we do not find such evidence. Our empirical results indicate that abnormal short-term shorting flows have little predictive ability for future returns. Combined with our earlier findings, these results suggest that the persistent shorting over an extended period of time, not a temporary increase in shorting, predicts negative future returns.

Broadly speaking, short sellers may be able to predict future returns either because they possess private information or because they are better at processing and exploiting public information. To differentiate between these two possibilities, we examine whether shorting flows are abnormally high prior to negative news announcements. We measure negative news using the following three proxies: negative earnings surprises, analyst downgrades, and large insider sales. We find no evidence of abnormally high shorting flows during the five days preceding these negative news. This finding does not support the hypothesis that short sellers, as a group, possess private information about negative news announcements.

Our results so far suggest that, during our sample period, short sellers' predictive ability is more likely to arise from long-term, public information than from short-term, private information. To investigate what kind of long-term, public information short sellers trade on, we examine 20 prominent anomaly variables (e.g., momentum, asset growth, and gross profitability) that prior literature has shown to be significantly related to the cross-section of stock returns. If short sellers are sophisticated investors who understand the predictable returns associated with these variables, we would expect short sellers to engage in the arbitrage of these anomalies. Consistent with short sellers trading on anomalies, we find that shorting flows are significantly higher among stocks in the short leg of the anomalies, e.g., past losers, high asset-growth stocks, and low-profitability stocks. The anomaly variables considered in our study are persistent, and their informational content is typically impounded into prices with significant delays. As such, short sellers' trading on anomalies helps explain why shorting flows predict both short- and long-run returns and why long-term, persistent shorting flows predict future returns better than short-term shorting flows.

We have shown that shorting flows predict negative future stock returns during 2010–2015. Moreover, this predictability is longer term than what prior studies (Boehmer et al., 2008; Diether et al., 2009) have found. To provide a more direct comparison with previous sample periods, we repeat our analyses using the 2005–2007 Regulation SHO data. We find that shorting flows significantly and negatively predict short-run stock returns during 2005–2007. However, there is little evidence that heavily shorted stocks significantly underperform lightly shorted stocks beyond the initial holding period of a month. This result is in stark contrast to what we find for the 2010–2015 period, in which the predictability decays slowly and persists for a year. In addition, we find that short-term shorting flows are more informative than long-term shorting flows and that abnormal short-term shorting flows significantly predict negative future stock returns. These results are again contrary to those for 2010–2015. Finally, we find some evidence that short sellers trade on prominent anomalies during 2005–2007, but to a much lesser extent than during 2010–2015. Overall, our results indicate that the predictive ability of shorting flows is much longer-term during 2010–2015 than during 2005–2007, suggesting that short sellers, as a group, may have shifted their focus from trading on short-term information to trading on long-term information.

Our paper contributes to the literature in several ways. First, we examine the predictive ability of shorting flows during a sample period in which daily short volume data are disclosed in real time. This new data set provides a unique opportunity to examine the informativeness of short sales and the extent to which the market is informationally efficient. Our results suggest that short sellers continue to be informed during 2010–2015, and that the market is slow to incorporate their information into prices.

Second, prior studies of daily shorting flows (Boehmer et al., 2008; Diether et al., 2009) focus on short-term predictability. This focus is motivated by the high-frequency nature of the data, the relatively short sample period, and the implicit assumption that short sellers are short-term traders. We extend these studies by providing a first examination of the informativeness of long-term shorting flows and abnormal shorting flows. We show that, during our sample period, long-term shorting flows are associated with greater return predictability than short-term shorting flows. Moreover, abnormal shorting flows do not predict future returns or anticipate negative news. These results are consistent with short sellers trading on long-term information that is gradually impounded into prices. Our findings are different from prior studies (and from our own analysis of the RegSHO data) in part because our sample period is more recent. We argue that the combination of a substantial increase in short-sale volume, the public disclosure of daily short-sale data, and a stricter regulatory environment regarding the release of nonpublic information in more recent time periods explains why short sellers now rely more heavily on long-term, public information as opposed to short-term, private information when making shorting decisions.

Third, our paper adds to the literature examining whether short sellers exploit anomalies. Prior studies in this area rely on monthly short interest data. For example, Dechow et al. (2001) find that short sellers target companies that are overpriced based on fundamental ratios such as price to earnings and market to book. Drake et al. (2011) show that short sellers trade on 11 items of fundamental information. Hirshleifer et al. (2011) present evidence that investors engage in short arbitrage of the accrual anomaly. Hanson and Sunderam (2014) find that short sellers exploit the momentum and value anomalies. We contribute to this literature by studying daily shorting activities instead of monthly short interest and by examining a larger number of anomalies.

Fourth, our paper contributes to the regulatory debate on the benefits and costs of real time public disclosure of short-sale activities. Since the financial crisis of 2007–2009, many countries around the world have increased disclosure requirements for short-sale transactions. Countries in the European Union, for example, require real time disclosure of large short positions. There is a heated debate about the efficacy of such disclosures among practitioners, regulators, and academics (Securities and Exchange Commission (SEC), 2014; Duong et al., 2015; Jones et al., 2016; Galema and Gerritsen, 2018). In particular, finance theories suggest that short-sale disclosures can provide a coordination mechanism for manipulative shorting attacks (Brunnermeier and Oehmke, 2014). The regulators are also concerned about the possibility of herding and copy-cat trading, which may discourage informed shorting and reduce price informativeness (SEC, 2014). We contribute to this debate by showing that the public disclosure of daily short volume does not seem to destabilize the market. Further, we find that short sellers continue to be informed during 2010–2015, but they appear to have shifted from trading on short-term private information to trading on long-term public information.

Finally, our paper is closely related to several papers in the recent short-selling literature. Blocher et al. (2018) show that there are two distinct types of short sellers: short traders, who act on short-lived information; and short investors, who trade on long-lived information. The presence of long-horizon short sellers, i.e., short investors, is consistent with our finding that shorting flows predict long-run stock returns. Reed et al. (2018) examine the relation between trading venue choice and shorting informativenss, and they find that exchange short sales are more informative about future prices than dark pool short sales. Kahraman and Pachare (2018) and Hu (2017) examine the effects of increasing frequency of public disclosure of short interest data. Kahraman and Pachare (2018) find that, with more frequent disclosure, short sellers' information is incorporated into prices faster, improving informational efficiency. Hu (2017) shows that the greater market transparency increases firm voluntary disclosure.

The remainder of the paper proceeds as follows. Section 2 describes the sample and data. Section 3 presents the empirical results. Section 4 concludes.

2. Data, sample, and summary statistics

This section presents our data, sample, and summary statistics. Section 2.1 discusses the sources of our data for short sales, stock returns, and other stock characteristics. Section 2.2 presents the summary statistics of our sample stocks.

2.1. Data and sample

We obtain daily aggregate short-sale volume for individual equity securities from Financial Industry Regulatory Authority, Inc., which is a private corporation that acts as a self-regulatory organization. FINRA is the successor to the National Association of Securities Dealers, Inc. (NASD), and the member regulation, enforcement, and arbitration operations of the New York Stock Exchange. In an effort to increase transparency on short-sale activities, the Securities and Exchange Commission requested FINRA to make security-level aggregate short-sale volume data publicly available on a daily basis. The data set includes the trade date, ticker, market identifier, aggregate short-sale volume, and aggregate total volume for each security during regular trading hours. FINRA publishes these data each day on its website after the end of regular trading hours, and, in rare instances, the data are released during the next business day.[3]

Short-sale transactions for a stock can occur in multiple markets. We aggregate the short volume across different markets for each stock on each day. If the aggregate short volume is missing, we replace it with zero. Stocks that have no short-sale volume throughout our sample period are excluded from our analysis. We follow prior studies (Boehmer et al., 2008; Diether et al., 2009) and construct short volume ratio as total short-sale volume divided by total trading volume for each stock on each day.[4]

We obtain daily stock returns, share price, shares outstanding, and other stock characteristics from the Center for Research in Security Prices (CRSP). We merge the FINRA data with the CRSP database by using the ticker symbol. We obtain Fama and French (1996) three factors, Fama and French (2015) five factors, and the momentum factor from Kenneth French's website.[5] We obtain the Hou's et al. (2015) *q*-factors from Lu Zhang. Our sample includes all common stocks (with a CRSP share code of 10 or 11) listed on NYSE, AMEX, and NASDAQ over the period from January 2010 to December 2015.

We obtain institution holdings from the Thomson 13F database. We define institutional ownership as the total number of shares held by institutions divided by the total number of shares outstanding. We obtain quarterly earnings and earnings announcement dates from Compustat, analyst recommendations from Institutional Brokers' Estimate System (I/B/E/S), and insider trades from Thomson Insider Trading Database. We estimate idiosyncratic volatility for each stock using past one year of daily returns based on the market model. We compute Amihud's illiquidity based on Amihud (2002). We obtain data necessary to construct the 20 anomaly variables (listed in the Appendix) from CRSP, Compustat, and I/B/E/S.

2.2. Summary statistics

Panel A of Table 1 presents the summary statistics for our sample stocks. The average daily short-sale volume is over 152,000 shares per day, which accounts for about 36% of the total trading volume. The median short volume ratio is also about 36%, suggesting that the variable is not significantly skewed. The average short volume ratio during our sample period is much higher than those reported in Boehmer et al. (2008) and Diether et al. (2009), indicating that shorting has become more prevalent.[6] The average market capitalization is $4.54 billion. The average idiosyncratic volatility is 2.29% per day, and the average institutional ownership is 61%. The average number of stocks in our sample is 3766 per day.

Panel B presents the short volume, total volume, and short volume ratio by size quintiles. As expected, we find that both short-sale volume and total trading volume increase monotonically with firm size. More importantly, we show that the short volume ratio is also increasing in firm size. That is, short sales account for a greater percentage of total trading volume for larger stocks. Nevertheless, shorting is still prevalent even among the smallest stocks, accounting for nearly 26% of their total trading volume.

3. Empirical results

This section presents our empirical results. Section 3.1 presents the baseline results. Section 3.2 examines the role of limits to arbitrage. Section 3.3 presents the long-run performance results. Section 3.4 examines long-term shorting flows. Section 3.5 presents the results for abnormal short-term shorting flows. Section 3.6 examines whether shorting flows predict negative news events. Section 3.7 investigates whether short sellers trade on anomalies. Section 3.8 examines the Regulation SHO data for the period 2005–2007. Section 3.9 presents the results of robustness tests.

3.1. Baseline results

We examine the predictive ability of daily shorting flows by following the methodology of Boehmer et al. (2008). Specifically, we form quintile portfolios each day based on prior five days of average short volume ratio. In our main analyses, we skip one day and hold the portfolios for 20 days, i.e., from day 2 to day 21. We skip one day (i.e., day 1) to eliminate any possible microstructure effects. Because the first day after portfolio formation is effectively

[3] See http://regsho.finra.org/regsho-Index.html. The FINRA data are also available on third-party websites, including http://www.shortvolume.com/ and http://shortstockvolume.com/.

[4] The total trading volume is also from FINRA to ensure consistency.

[5] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] Boehmer et al. (2008) report that short selling accounts for 12.9% of the NYSE trading volume during 2000–2004. Diether et al. (2009) report that short sales represent 23.9% of NYSE and 31.3% of Nasdaq share volume during 2005.

Table 1
Summary statistics.
This table presents the summary statistics. The short volume and total volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks [with a Center for Research in Security Prices (CRSP) share code of 10 or 11] listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. Share price, stock returns, market returns, and shares outstanding are from CRSP. Short volume ratio is the ratio of short volume to total volume. Firm size is in millions of dollars. IVOL is idiosyncratic volatility of stock returns, estimated from the market model using daily returns. Illiquidity (ILLIQ), constructed based on Amihud (2002), is the absolute daily return divided by dollar trading volume and then winsorized at 99%. Institutional ownership (IO) is the fraction of shares owned by institutional investors, calculated using the Thomson 13F institutional holdings database. Number of stocks is the number of stocks per day. Our sample contains 1510 trading days.

Panel A: Full sample

Variable	Mean	Standard deviation	25th percentile	50th percentile	75th percentile
Short volume (thousands of shares)	152.32	862.84	2.74	17.04	80.72
Total volume (thousands of shares)	411.00	2277.01	15.35	64.42	246.64
Short volume ratio (percent)	36.63	22.04	21.16	36.52	50.95
Price (dollar)	27.52	73.17	6.15	15.82	34.38
Firm size (millions of dollars)	4540.47	19417.61	111.84	494.38	2143.75
IVOL (percent)	2.29	1.41	1.32	1.90	2.83
ILLIQ ($\times 10^6$)	1.877	10.158	0.001	0.007	0.075
IO	0.61	0.30	0.38	0.67	0.84
Number of stocks	3766	110	3678	3750	3813

Panel B: By size quintiles

Variable	Q1 (small)	Q2	Q3	Q4	Q5 (large)
Short volume (thousands of shares)	16.77	32.22	62.67	132.77	519.69
Total volume (thousands of shares)	73.89	100.09	166.18	318.26	1259.52
Short volume ratio (percent)	25.90	34.74	38.79	41.98	42.30

the announcement day for the short-sale volume data, we also separately examine the return for this day.

The portfolios are rebalanced daily, so there is overlap in holding period returns. To deal with this overlap, we use a calendar-time portfolio approach to calculate average daily returns and conduct inferences. We calculate both equal- and value-weighted returns and then estimate one-, three-, and four-factor alphas based on the Capital Asset Pricing Model (CAPM) and Fama and French (1996) three-factor and Carhart (1997) four-factor models. In addition to alphas for each shorting portfolio, we also report the difference in alphas between the two extreme shorting portfolios.

Table 2 presents the results. In Panel A, the holding period is day 1, i.e., the day after portfolio formation. As stated earlier, although this day is usually excluded by prior studies (Boehmer et al., 2008; Diether et al., 2009), we report the results for this day because of its significance as the announcement day for the short volume data. If the market is efficient, then any information contained in the public daily short volume data should be fully incorporated into price on this day. We find that heavily shorted stocks significantly underperform lightly shorted stocks on day 1. This finding is robust whether we look at equal- or value-weighted portfolios and whether we use one-, three-, or four-factor alphas. The result is highly statistically significant with t-statistics around 4 across all specifications. However, the economic magnitude of the underperformance by heavily shorted stocks is relatively small, ranging from 3.4 to 4 basis points. This result suggests that the immediate market reaction to the public shorting information is likely to be incomplete.

Panel B presents the results for the holding period from day 2 to day 21. This is the same holding period examined by Boehmer et al. (2008). If the market is informationally efficient, then we would expect the predictive content of shorting flows to be impounded into prices on day 1 and, as such, returns from day 2 through day 21 should not be predictable from past shorting flows. The results in Panel B are inconsistent with this hypothesis. We find that heavily shorted stocks continue to underperform lightly shorted stocks over this period. For example, using the Fama and French three-factor model as the benchmark model, we find that heavily-shorted stocks underperform lightly-shorted stocks by an annualized risk-adjusted return of 12.6% (t-statistic = 6.00) for equal-weighted portfolios and by 6.0% (t-statistic = 4.03) for value-weighted portfolios. The results are highly significant for both equal- and value-weighted portfolios, but more pronounced for equal-weighted portfolios.

We find, similar to Boehmer et al. (2008), that the performance difference between the high- and low-shorting quintiles is primarily driven by the outperformance of low-shorting quintile instead of the underperformance of high-shorting quintile. Indeed, the low-shorting quintile exhibits significantly positive alphas, while the high-shorting quintile has insignificant alphas. Overall, our results in Table 2 suggest that short sellers are well informed during our sample period and that the market is slow to incorporate public shorting information into prices.

3.2. Limits to arbitrage

One possible explanation for the slow market reaction to public shorting information is limits to arbitrage (Shleifer and Vishny, 1997; Pontiff, 2006). To provide evidence on this possibility, we examine whether the predictive ability of daily shorting flows is stronger among stocks with greater limits to arbitrage. Specifically, we sort our sample stocks into high- and low-categories by firm

Table 2
Daily shorting flows and future stock returns.
This table presents the equal- and value-weighted average daily returns of quintile portfolios sorted based on past five-day short volume ratios. The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. On each trading day, we sort stocks into quintiles based on their past five-day average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The short volume ratio is short volume divided by total volume. Panel A reports the average return for Day 1 after portfolio formation. Panel B reports the average return from Day 2 to Day 21 after portfolio formation. We estimate one-, three-, and four-factor alphas based on the market model, the Fama and French (1996) model, and the Carhart (1997) model. Alphas are expressed in percent per day. Numbers in parentheses are *t*-statistics.

Shorting quintile	Equal weight			Value weight		
	One-factor α	Three-factor α	Four-factor α	One-factor α	Three-factor α	Four-factor α
Panel A: Day 1						
1 (lowest)	0.040	0.044	0.044	0.034	0.036	0.035
	(3.82)	(5.03)	(5.04)	(4.14)	(4.55)	(4.49)
2	0.008	0.015	0.016	0.016	0.015	0.015
	(0.72)	(2.63)	(2.72)	(2.86)	(2.72)	(2.65)
3	−0.003	0.005	0.006	−0.002	−0.003	−0.003
	(−0.29)	(1.00)	(1.25)	(−0.56)	(−0.81)	(−0.90)
4	−0.011	−0.003	−0.001	−0.007	−0.007	−0.007
	(−1.05)	(−0.60)	(−0.18)	(−2.06)	(−2.01)	(−2.00)
5 (highest)	−0.001	0.007	0.010	−0.006	−0.004	−0.003
	(−0.12)	(1.68)	(2.58)	(−1.40)	(−0.96)	(−0.76)
5 - 1	−0.040	−0.037	−0.034	−0.040	−0.040	−0.038
	(−4.05)	(−3.94)	(−3.76)	(−4.19)	(−4.18)	(−4.06)
Panel B: Day 2 to Day 21						
1 (lowest)	0.047	0.052	0.052	0.021	0.022	0.022
	(4.76)	(6.36)	(6.38)	(4.09)	(4.92)	(4.92)
2	0.004	0.011	0.012	0.007	0.006	0.006
	(0.37)	(2.22)	(2.32)	(1.97)	(1.75)	(1.79)
3	−0.006	0.002	0.003	−0.003	−0.004	−0.004
	(−0.58)	(0.46)	(0.79)	(−1.53)	(−1.74)	(−1.80)
4	−0.009	−0.001	0.001	−0.002	−0.002	−0.002
	(−0.95)	(−0.38)	(0.15)	(−1.01)	(−1.10)	(−1.07)
5 (highest)	−0.006	0.002	0.005	−0.004	−0.002	−0.001
	(−0.61)	(0.65)	(1.7)	(−1.16)	(−0.62)	(−0.37)
5 - 1	−0.053	−0.050	−0.047	−0.025	−0.024	−0.023
	(−5.94)	(−6.00)	(−5.88)	(−4.00)	(−4.03)	(−3.92)

size, illiquidity, idiosyncratic volatility (IVOL), and institutional ownership (IO). We independently sort sample stocks based on prior five days of shorting activity and examine the performance of shorting portfolios within each limits-to-arbitrage category.

Table 3 presents the results of this analysis. For brevity, we report only the results for Fama and French three-factor alphas. The results for one- and four-factor alphas are qualitatively similar. Panel A reports the results for size. We find that, for both large and small stocks, the high-shorting quintile significantly underperforms the low-shorting quintile. Consistent with the limits-to-arbitrage argument, we find that the magnitude of this underperformance is considerably larger among small stocks than among large stocks. For example, for small stocks, the high-shorting quintile underperforms the low-shorting quintile by 6.3 basis points per day (*t*-statistic = 5.99) for equal-weighted portfolios and 5.4 basis points per day (*t*-statistic = 4.87) for value-weighted portfolios. In comparison, for large stocks, the high-shorting quintile underperforms the low-shorting quintile by 2.2 basis points per day (*t*-statistic = 4.95) for equal-weighted portfolios and 1.3 basis points per day (*t*-statistic = 2.17) for value-weighted portfolios. The difference between small and large stocks is economically and statistically significant. Overall, we find that shorting flows predict future returns for both small and large stocks and that the predictive ability is stronger among small stocks.[7]

The results for the other three limits-to-arbitrage proxies (reported in Panels B, C, and D) are qualitatively similar. We find that, consistent with the limit-to-arbitrage argument, the negative relation between daily shorting flows and future stock returns is more pronounced among illiquid, high IVOL, and low IO stocks. Nevertheless, the predictability of daily shorting flows remains significant for liquid, low IVOL, and high IO stocks. For example, looking at equal-weighted returns, we find that the high-shorting quintile underperforms the low-shorting quintile by 7.2 basis points per day (*t*-statistic = 6.46) among high IVOL stocks and 2.6 basis points per day (*t*-statistic = 6.37) among low IVOL stocks. Similarly, the high-shorting quintile underperforms the low-shorting quintile by 5.3 basis points per day (*t*-statistic = 5.05) among illiquid stocks and 1.9 basis points per day (*t*-statistic = 4.05) among liquid stocks. Finally, the high-shorting quintile underperforms the low-shorting quintile by 6.4 basis points per day (*t*-statistic = 6.52) among low IO stocks and 3.6 basis points per day (*t*-statistic = 6.48) among high IO stocks. This last

[7] Because the analyst coverage is sparser and public information is less readily available for small stocks, this finding is also consistent with the idea that short sellers are relatively more informed about small stocks.

Table 3
Daily shorting flows and future stock returns: by firm characteristics.

This table presents the equal- and value-weighted average daily returns of quintile portfolios sorted based on past five-day short volume ratios by firm characteristics. The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. On each trading day, we independently sort stocks into quintiles based on short volume ratio and two equal-size portfolios based on each firm characteristic [size in Panel A, idiosyncratic volatility (IVOL) in Panel B, illiquidity in Panel C, and institutional ownership (IO) in Panel D]. The holding period is from Day 2 to Day 21 after portfolio formation. The short volume ratio is short volume divided by total volume. IVOL is idiosyncratic volatility of stock returns, estimated from the capital asset pricing model using daily returns. Illiquidity (ILLIQ), constructed based on Amihud (2002), is the absolute daily return divided by dollar trading volume and then winsorized at 99%. Institutional ownership is the fraction of shares owned by institutional investors, calculated using the Thomson 13F institutional holdings database. We estimate three-factor alphas based on the Fama and French (1996) model. Alphas are expressed in percent per day. Numbers in parentheses are *t*-statistics.

Panel A: Size

Shorting	Equal weight			Value weight		
quintile	Small	Large	Difference	Small	Large	Difference
1 (lowest)	0.076	0.016	0.060	0.047	0.012	0.035
	(7.23)	(5.32)	(5.51)	(5.19)	(3.05)	(3.52)
2	0.027	0.002	0.025	0.013	−0.003	0.016
	(2.91)	(0.67)	(2.66)	(2.03)	(−1.10)	(2.34)
3	0.007	−0.003	0.011	−0.002	−0.002	−0.001
	(0.85)	(−1.13)	(1.20)	(−0.34)	(−0.80)	(−0.11)
4	0.003	−0.006	0.009	−0.010	−0.003	−0.006
	(0.35)	(−1.93)	(1.06)	(−1.37)	(−1.39)	(−0.85)
5 (highest)	0.013	−0.006	0.019	−0.007	−0.001	−0.006
	(1.64)	(−1.53)	(2.16)	(−0.82)	(−0.32)	(−0.62)
5–1	−0.063	−0.022	−0.041	−0.054	−0.013	−0.041
	(−5.99)	(−4.95)	(−3.77)	(−4.87)	(−2.17)	(−3.34)

Panel B: IVOL

Shorting	Equal weight			Value weight		
quintile	Low IVOL	High IVOL	Difference	Low IVOL	High IVOL	Difference
1 (lowest)	0.036	0.067	−0.032	0.015	0.022	−0.007
	(9.46)	(5.60)	(−2.47)	(3.53)	(2.43)	(−0.67)
2	0.018	0.010	0.008	0.001	0.003	−0.001
	(5.83)	(0.98)	(0.66)	(0.46)	(0.27)	(−0.13)
3	0.012	−0.003	0.015	−0.002	−0.012	0.010
	(4.18)	(−0.36)	(1.39)	(−0.83)	(−0.95)	(0.76)
4	0.009	−0.009	0.019	0.000	−0.015	0.015
	(3.07)	(−1.04)	(1.69)	(0.01)	(−1.14)	(1.07)
5 (highest)	0.010	−0.005	0.014	0.003	−0.034	0.037
	(2.52)	(−0.51)	(1.33)	(0.93)	(−2.78)	(2.85)
5–1	−0.026	−0.072	0.046	−0.012	−0.056	0.044
	(−6.37)	(−6.46)	(4.51)	(−2.05)	(−4.12)	(3.15)

Panel C: Illiquidity

Shorting	Equal weight			Value weight		
quintile	Liquid	Illiquid	Difference	Liquid	Illiquid	Difference
1 (lowest)	0.012	0.074	−0.062	0.011	0.042	−0.031
	(3.38)	(7.01)	(−5.65)	(2.85)	(5.38)	(−3.47)
2	0.001	0.029	−0.028	−0.002	0.015	−0.017
	(0.26)	(3.18)	(−2.93)	(−0.84)	(2.40)	(−2.61)
3	−0.003	0.014	−0.017	−0.001	0.002	−0.003
	(−0.92)	(1.74)	(−1.94)	(−0.58)	(0.27)	(−0.43)
4	−0.006	0.011	−0.017	−0.002	−0.001	−0.001
	(−1.68)	(1.50)	(−2.04)	(−0.95)	(−0.16)	(−0.15)
5 (highest)	−0.007	0.021	−0.028	−0.001	−0.002	0.001
	(−1.66)	(2.79)	(−3.09)	(−0.37)	(−0.20)	(0.03)
5–1	−0.019	−0.053	0.034	−0.012	−0.043	0.031
	(−4.05)	(−5.05)	(3.04)	(−2.06)	(−4.39)	(2.71)

Panel D: IO

Shorting	Equal weight			Value weight		
quintile	Low IO	High IO	Difference	Low IO	High IO	Difference
1 (lowest)	0.079	0.030	0.049	0.036	0.016	0.021
	(7.78)	(8.15)	(4.64)	(4.76)	(3.64)	(2.35)
2	0.026	0.013	0.012	0.011	0.007	0.004
	(2.95)	(4.86)	(1.38)	(1.23)	(2.03)	(0.39)
3	0.009	0.006	0.003	−0.010	0.004	−0.014
	(1.22)	(1.94)	(0.44)	(−1.52)	(1.25)	(−1.67)
4	0.003	0.001	0.002	−0.011	0.004	−0.015
	(0.48)	(0.32)	(0.29)	(−2.32)	(1.22)	(−2.20)
5 (highest)	0.015	−0.005	0.021	−0.005	0.000	−0.005
	(2.61)	(−1.24)	(2.99)	(−0.77)	(0.06)	(−0.64)
5–1	−0.064	−0.036	−0.028	−0.041	−0.015	−0.026
	(−6.52)	(−6.48)	(−2.61)	(−4.15)	(−2.73)	(−2.40)

Table 4
Daily shorting flows and future stock returns: long-run performance.
This table presents the cumulative equal- and value-weighted Fama–French three-factor risk-adjusted returns of the portfolios sorted based on past five-day short volume ratios. The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. On each trading day, we sort stocks into quintiles based on their past five-day average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The holding period varies from Day 22 to Day 60, Day 61 to Day 90, Day 91 to Day 120, and Day 121 to Day 252 after portfolio formation. The short volume ratio is short volume divided by total volume. Returns are in percent. Numbers in parentheses are Newey-West adjusted t-statistics.

Shorting quintile	Day (22, 60)	Day (61, 90)	Day (91, 120)	Day (121, 252)
Panel A: Equal weight				
1 (lowest)	0.67	0.63	0.64	2.99
	(1.48)	(1.88)	(1.88)	(1.90)
2	0.02	−0.03	0.07	0.39
	(0.07)	(−0.14)	(0.41)	(0.52)
3	−0.09	−0.11	−0.11	−0.07
	(−0.55)	(−0.82)	(−0.84)	(−0.13)
4	−0.09	−0.15	−0.18	−0.46
	(−0.63)	(−1.45)	(−1.59)	(−1.15)
5 (highest)	−0.03	−0.07	−0.11	−0.14
	(−0.26)	(−0.91)	(−1.58)	(−0.43)
5–1	−0.70	−0.70	−0.76	−3.13
	(−1.76)	(−2.36)	(−2.52)	(−2.33)
Panel B: Value weight				
1 (lowest)	0.39	0.48	0.48	1.20
	(2.74)	(4.67)	(4.33)	(3.88)
2	0.21	0.24	0.17	0.12
	(2.19)	(3.20)	(2.47)	(0.62)
3	0.10	0.03	0.00	−0.24
	(1.22)	(0.47)	(0.01)	(−1.11)
4	−0.04	−0.07	0.06	0.03
	(−0.51)	(−1.25)	(1.00)	(0.12)
5 (highest)	−0.02	0.03	−0.05	−0.09
	(−0.20)	(0.34)	(−0.65)	(−0.24)
5–1	−0.41	−0.46	−0.53	−1.29
	(−2.32)	(−3.81)	(−3.74)	(−2.87)

result is particularly noteworthy, as previous studies based on monthly short interest data (e.g., Asquith et al., 2005) find that short sellers are not informed about future returns among high IO stocks. Overall, we find results consistent with the limit-to-arbitrage argument. That is, the negative relation between daily shorting flows and future stock returns is more pronounced among small, illiquid, high IVOL, and low IO stocks.

3.3. Long-run performance

Consistent with Boehmer et al. (2008) and Diether et al. (2009), we interpret the predictive ability of daily shorting flows as suggesting that short sellers are informed and that they bring prices closer to the fundamentals. However, this predictability could also be induced by destabilizing shorting. In particular, the public disclosure of short sale data may facilitate coordination among manipulative short sellers (Brunnermeier and Oehmke, 2014), whose shorting activities would drive stock prices below fundamental values. In addition, destabilizing shorting could arise as a result of crowding (Stein, 2009). Given the well-documented results of Boehmer et al. (2008) and Diether et al. (2009), one would expect that public disclosure of high short volume on a stock will attract more investors to short the stock. Such trading has no anchor in fundamentals and, therefore, if too many investors act on this information, prices will overshoot. Both manipulative shorting and crowded shorting will cause prices to decline in the short run, giving rise to the short-term predictability of daily shorting flows, and revert to the fundamentals in the long run, causing long-run reversal. In contrast, if the short-run predictability of daily shorting flows is due to informed shorting, we would not expect to find long-run reversal.

To differentiate between stabilizing (i.e., informed) shorting and destabilizing shorting, we examine the long-run performance of shorting portfolios up to a year. Table 4 presents the results. We continue to sort stocks based on past five days of shorting activity, but instead of holding the portfolios from day 2 to day 21, we track their performance from day 22 through day 252. Specifically, we examine four distinct holding periods, from day 22 to day 60, from day 61 to day 90, from day 91 to day 120, and from day 121 to day 252. We report the cumulative Fama and French three-factor alphas for each sub-period.[8]

Results in Table 4 indicate that heavily shorted stocks continue to underperform lightly shorted stocks during each of the holding periods we examine. For example, stocks in the highest shorting quintile underperform those

[8] We first estimate the full sample Fama and French three-factor model for each stock using their daily returns and then add up the residuals and the intercept as risk-adjusted daily returns. For each holding period, we then compute the cumulative risk-adjusted returns for each stock. The number of lags for the Newey and West adjustment depends on the length of each holding period.

in the lowest shorting quintile by 0.70% (t-statistic = 2.36) during day 61 to day 90 for equal-weighted portfolios and by 0.46% (t-statistic = 3.81) for value-weighted portfolios. These magnitudes are lower than those observed during the initial holding period (i.e., from day 2 to day 21) but are nevertheless economically and statistically significant. The return continuation extends well into the second half of the year, i.e., day 121 to day 252, when stocks in the highest shorting quintile underperforms those in the lowest shorting quintile by 3.13% (t-statistic = 2.33) for equal-weighted portfolios and by 1.29% (t-statistic = 2.87) for value-weighted portfolios. In contrast, Boehmer et al. (2008) show that the predictive ability of shorting flows largely dissipates after 20 days. Diether et al. (2009) show that the predictive power of daily shorting flows extends to just five days after portfolio formation date. Overall, we show that the predictability of daily shorting flows decays slowly and persists for a year. The absence of long-run reversal is consistent with informed shorting, while inconsistent with destabilizing shorting.

3.4. Long-term shorting flows

Previous studies of daily shorting flows focus exclusively on short-term predictability. For example, Diether et al. (2009) examine whether past 1-day shorting predicts returns over the subsequent two to five days. Boehmer et al. (2008) examine the predictive ability of past 5-day shorting flows for returns over the next 20 days. Accordingly, these studies conclude that short sellers primarily trade on short-term information. For example, Diether et al. (2009, p.576) argue that their results "are consistent with short sellers trading on short-term overreaction of stock prices" and suggest that "academics generally share the view that short sellers help markets correct short-term deviations of stock prices from fundamental value."

However, our finding that the predictive ability of daily shorting flows decays slowly and persists for a year strongly suggests that short sellers could be trading on long-term information that is gradually incorporated into prices. To provide more evidence on this possibility, we examine the informativeness of long-term shorting flows. If short sellers specialize in trading on short-term information, we would expect short-term shorting flows to exhibit stronger predictive power for future stock returns than long-term shorting flows. On the other hand, if short sellers trade on long-term information that is gradually impounded into prices, we would expect long-term shorting flows to predict future returns at least as well as the short-term shorting flows.

We measure long-term shorting flows over the 20- or 60-day period prior to the past five days, and, for ease of exposition, we refer to them as monthly and quarterly shorting flows, respectively. We sort sample stocks into quintile portfolios based on these long-term shorting flows and examine their performance over the subsequent 20 trading days after skipping one day. Panel A of Table 5 presents the results for monthly shorting flows. We find strong evidence that heavily shorted stocks significantly underperform lightly shorted stocks. For example, for three-factor alphas, we find that the high-shorting quintile underperforms the low-shorting quintile by 5.8 basis points per day (t-statistic = 5.67) for equal-weighted portfolios and 2.8 basis points per day (t-statistic = 3.7) for value-weighted portfolios. The results based on quarterly shorting flows (Panel B) are qualitatively similar and quantitatively larger. For three-factor alphas, the high-shorting quintile underperforms the low-shorting quintile by 6.2 basis points per day (t-statistic = 5.55) for equal-weighted portfolios and 3.5 basis points per day (t-statistic = 3.9) for value-weighted portfolios. In comparison, Panel B of Table 2 shows that, when sorting on past five-day shorting flows, the corresponding spreads in three-factor alphas are 5.0 basis points per day (t-statistic = 6.00) for equal-weighted portfolios and 2.4 basis points per day (t-statistic = 4.03) for value-weighted portfolios. That is, the magnitude of the underperformance associated with long-term shorting flows is larger than that associated with short-term shorting flows.[9]

In summary, we show that long-term shorting flows significantly predict negative future returns. Moreover, past-month and past-quarter shorting flows are associated with greater return predictability than past-week shorting flows, suggesting that long-term shorting flows are at least as informative as (or even more informative than) short-term shorting flows. This finding lends support to the hypothesis that short sellers trade on long-term information that is gradually incorporated into prices.

One might ask why short sellers trade on long-term information if their investment horizons are relatively short (Boehmer et al., 2008; Diether et al., 2009). In estimating the investment horizons of short sellers, previous studies tend to focus on the average duration across all stocks and all short sellers. However, there is considerable heterogeneity across both stocks and short sellers. Once we take this heterogeneity into account, we find that the duration of short positions is not always as short as previously thought. We follow Boehmer et al. (2008) and estimate the duration of short positions from short-sale volume and short interest data. Untabulated analysis indicates that although on average short sellers hold their short positions only for 28 days, this duration measure exhibits considerable variation across stocks. While the 10th percentile of short position duration is only nine days, the 90th percentile is 125 days, which is almost six months. This means that for many stocks, the average duration of the short positions is much longer than previously shown. In addition to heterogeneity among stocks, significant heterogeneity also exists among short sellers. It is true many short sellers have short investment horizons (for example, high frequency traders typically initiate and close their short positions within a day), but many short sellers including those who focus on "forensic accounting" have "investment horizons ranging from several months to several years" (Akbas et al., 2017 p. 457; Karpoff and Lou, 2010). Blocher et al. (2018) also show that short sellers are comprised of both short traders and short investors. The long-term short

[9] In Table A9 of the Internet Appendix, we show that the difference in return spread between long- and short-term shorting flows is statistically significant for equal-weighted portfolios and insignificant for value-weighted portfolios.

Table 5
Long-term shorting flows and future stock returns.
This table presents the daily equal- and value-weighted average future 20-day returns of the portfolios based on two long-term past shorting-flow measures: the average short volume ratio from Day −25 to Day −6 (Panel A) and the average short volume ratio from Day −65 to Day −6 (Panel B). The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. On each trading day, we sort stocks into quintiles based on their past average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The holding period is from Day 2 to Day 21 after portfolio formation. The short volume ratio is short volume divided by total volume. We estimate one-, three-, and four-factor alphas based on the market model, the Fama and French (1996) model, and the Carhart (1997) model. Alphas are expressed in percent per day. Numbers in parentheses are t-statistics.

Shorting quintile	Equal weight			Value weight		
	One-factor α	Three-factor α	Four-factor α	One-factor α	Three-factor α	Four-factor α
Panel A: $SHORT_{t-25,\ t-6}$						
1 (lowest)	0.050	0.054	0.054	0.026	0.028	0.027
	(4.70)	(5.83)	(5.74)	(3.92)	(4.53)	(4.44)
2	0.004	0.011	0.011	0.007	0.006	0.007
	(0.34)	(1.93)	(1.96)	(1.44)	(1.31)	(1.37)
3	−0.006	0.002	0.004	0.000	0.000	0.000
	(−0.54)	(0.60)	(1.03)	(0.07)	(−0.09)	(0.02)
4	−0.010	−0.002	0.000	−0.004	−0.005	−0.005
	(−1.02)	(−0.64)	(−0.05)	(−1.74)	(−1.93)	(−2.04)
5 (highest)	−0.012	−0.003	0.000	−0.002	0.000	0.000
	(−1.22)	(−0.82)	(0.02)	(−0.68)	(−0.12)	(0.09)
5–1	−0.062	−0.058	−0.053	−0.029	−0.028	−0.027
	(−5.67)	(−5.67)	(−5.51)	(−3.65)	(−3.70)	(−3.55)
Panel B: $SHORT_{t-65,\ t-6}$						
1 (lowest)	0.053	0.057	0.056	0.030	0.032	0.031
	(4.72)	(5.57)	(5.48)	(3.62)	(4.17)	(4.02)
2	0.003	0.010	0.011	0.009	0.009	0.009
	(0.24)	(1.70)	(1.72)	(1.51)	(1.45)	(1.51)
3	−0.004	0.004	0.006	0.001	0.000	0.000
	(−0.37)	(0.99)	(1.42)	(0.31)	(0.03)	(0.16)
4	−0.012	−0.004	−0.001	−0.002	−0.002	−0.002
	(−1.17)	(−1.05)	(−0.46)	(−0.62)	(−0.67)	(−0.60)
5 (highest)	−0.014	−0.005	−0.002	−0.005	−0.003	−0.003
	(−1.41)	(−1.20)	(−0.49)	(−1.27)	(−0.81)	(−0.77)
5–1	−0.066	−0.062	−0.057	−0.035	−0.035	−0.034
	(−5.60)	(−5.55)	(−5.39)	(−3.76)	(−3.90)	(−3.76)

sellers naturally have an incentive to trade on long-term information. Moreover, trading on long-term information is justified even for short-term traders if the information is incorporated into prices gradually.

3.5. Abnormal short-term shorting flows

Another way to investigate whether short sellers trade on short-term or long-term information is to examine the return predictability of abnormal short-term shorting flows. We follow Christophe et al. (2004) and construct abnormal short-term shorting flows as the difference between short-term shorting flows and long-term shorting flows. If short sellers possess short-term information and are able to time their trades, we would expect high abnormal shorting flows, i.e., large increases in shorting flows, to predict negative future stock returns. Put differently, because the significant holding cost associated with short selling, we would expect short sellers who possess short-lived information to place their trades just prior to the release of such information. On the other hand, if the predictability of daily shorting flows is primarily due to short sellers' trading on long-term information, then temporary changes in shorting flows will not necessarily predict future returns.

As in our previous analyses, our measure of short-term shorting flows is over the past week and our measure of long-term shorting flows is over the month or quarter prior to the past week. We define abnormal short-term shorting flows as the difference between short- and long-term shorting flows. We sort stocks into quintile portfolios based on these abnormal shorting flow measures and track their performance over the next 20 trading days after skipping one day.

Table 6 presents the results. In Panel A, the long-term shorting flow is measured during the month prior to the past week, and in Panel B the long-term shorting flow is measured during the quarter prior to the past week. We find no evidence that stocks with large positive abnormal shorting flows significantly underperform the stocks with large negative abnormal shorting flows. Abnormal shorting flows have little predictive power for future returns whether we measure long-term shorting over a month or a quarter, whether we examine equal- or value-weighted portfolios, and whether we use one-, three-, or four-factor alphas. For example, in Panel A, the high-abnormal shorting quintile underperforms the low-abnormal shorting quintile by 0.2 basis point per day (t-statistic = 0.47) for equal-weighted portfolios, and by 0.4 basis point per day (t-statistic = 1.17) for value-weighted portfolio. There are a couple of marginally significant

Table 6
Abnormal short-term shorting flows and future stock returns.
This table presents the daily equal- and value-weighted average future 20-day returns of the portfolios based on abnormal short-term shorting flows. We measure abnormal short-term shorting flows in two ways. The first (Panel A) is the difference between past five-day average short volume ratio and the average short volume ratio from Day −25 to Day −6. The second (Panel B) is the difference between past five-day average short volume ratio and the average short volume ratio from Day −65 to Day −6. The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. On each trading day, we sort stocks into quintiles based on abnormal shorting. Quintile 1 represents the portfolio with the lowest abnormal shorting, and Quintile 5 represents the portfolio with the highest abnormal shorting. The holding period is from Day 2 to Day 21 after portfolio formation. The short volume ratio is short volume divided by total volume. We estimate one-, three-, and four-factor alphas based on the market model, the Fama and French (1996) model, and the Carhart (1997) model. Alphas are expressed in percent per day. Numbers in parentheses are t-statistics.

Shorting quintile	Equal weight			Value weight		
	One-factor α	Three-factor α	Four-factor α	One-factor α	Three-factor α	Four-factor α
Panel A: $SHORT_{t-5,\,t-1} - SHORT_{t-25,\,t-6}$						
1 (lowest)	0.015	0.022	0.023	0.006	0.007	0.007
	(1.59)	(4.35)	(4.81)	(2.08)	(2.61)	(2.70)
2	0.005	0.012	0.013	0.000	0.000	0.000
	(0.48)	(2.75)	(3.07)	(0.18)	(−0.04)	(−0.09)
3	−0.002	0.005	0.006	−0.003	−0.003	−0.003
	(−0.23)	(1.21)	(1.52)	(−1.58)	(−1.86)	(−1.85)
4	−0.005	0.003	0.004	0.000	0.000	0.000
	(−0.52)	(0.65)	(1.04)	(−0.02)	(0.02)	(0.18)
5 (highest)	0.013	0.020	0.021	0.002	0.003	0.003
	(1.33)	(4.38)	(4.71)	(0.49)	(0.98)	(1.24)
5–1	−0.002	−0.002	−0.002	−0.005	−0.004	−0.004
	(−0.64)	(−0.47)	(−0.61)	(−1.27)	(−1.17)	(−1.06)
Panel B: $SHORT_{t-5,\,t-1} - SHORT_{t-65,\,t-6}$						
1 (lowest)	0.016	0.023	0.025	0.006	0.007	0.007
	(1.77)	(4.25)	(4.58)	(1.86)	(2.26)	(2.27)
2	0.007	0.014	0.015	0.002	0.001	0.000
	(0.73)	(3.24)	(3.53)	(0.77)	(0.59)	(0.43)
3	−0.002	0.005	0.006	−0.002	−0.002	−0.002
	(−0.25)	(1.21)	(1.55)	(−1.02)	(−1.26)	(−1.27)
4	−0.006	0.001	0.003	−0.001	−0.001	−0.001
	(−0.68)	(0.25)	(0.66)	(−0.52)	(−0.53)	(−0.33)
5 (highest)	0.010	0.018	0.020	−0.002	0.000	0.001
	(1.08)	(3.79)	(4.16)	(−0.54)	(−0.16)	(0.17)
5–1	−0.006	−0.005	−0.005	−0.008	−0.007	−0.006
	(−1.24)	(−1.07)	(−1.07)	(−1.82)	(−1.69)	(−1.49)

results in Panel B, but none of the results is significant at the 5% level. Moreover, the economic significance of the underperformance is small, ranging from 0.2 to 0.8 basis point per day.[10]

The combined results of Tables 5 and 6 suggest that persistently high shorting, not a temporary increase in shorting, predicts negative future returns. In other words, short-term shorting flows do not contain significant incremental information about future returns beyond that of long-term shorting flows. These findings are more consistent with short sellers trading on long-term information than trading on short-term information.

[10] Interestingly, we find that both Q1 and Q5 exhibit significantly positive three- and four-factor alphas for equal-weighted portfolios. Using a formal statistical test, we confirm that both Q1 and Q5 significantly outperform the middle portfolio (Q3)). We also sort stocks based on the absolute abnormal shorting flows and find that those with large absolute abnormal shorting flows significantly outperform those with small absolute abnormal shorting flows. Both of these results suggest that stocks with extreme abnormal shorting flows tend to outperform. This finding is driven by small stocks. Stocks in Q1 and Q5 are significantly smaller than those in the middle portfolios. More importantly, we find that both equal-weighted market portfolio and smallest size decile portfolio exhibit significant positive alphas. To conserve space, we present the results of these supplemental tests in Tables A10–A14 of the Internet Appendix.

3.6. News

Broadly speaking, short sellers' informational advantage may arise either from private information or from public information. If short sellers possess private information, they should be able to anticipate future news announcements. Alternatively, if they are simply better at processing and interpreting publicly available information, shorting activities will react to negative news rather than predicting it. To differentiate between these two possibilities, we examine whether shorting flows are abnormally high prior to negative news events. We measure negative news in three different ways, negative earnings surprises, analyst downgrades, and large insider sales. If short sellers are informed about impending negative news, shorting flows should increase significantly prior to the announcement of negative news. On the other hand, if short sellers derive their advantage primarily from processing public information, there should not be any significant change in shorting flows before these negative news events.

Panel A of Table 7 presents the results for earnings news. We measure earnings news based on standardized unexpected earnings (SUE), which is defined as the difference between current-quarter earnings and earnings four quarters ago scaled by lagged stock price. Each quarter, we

Table 7
Abnormal shorting flows prior to earnings surprises, analyst recommendation changes, and large insider trades.
This table presents the abnormal short-term shorting flows prior to earnings news (Panel A), analyst recommendation changes (Panel B), and large insider trades (Panel C). We measure abnormal short-term shorting flows in two ways. The first is the difference between past five-day average short volume ratio and the average short volume ratio from Day −25 to Day −6. The second is the difference between past five-day average short volume ratio and the average short volume ratio from Day −65 to Day −6. The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2010 to December 2015. The short volume ratio is short volume divided by total volume. We measure earnings news by using the standardized unexpected earnings (SUE). Decile 10 represents good news and Decile 1 represents bad news. We scale the share volume of each insider trade by total shares outstanding and define large insider sale (purchase) as those ranked in the top five percentiles among all insider trades. Quarterly earnings and earnings announcement dates are from Compustat. Analyst recommendations are from Institutional Brokers' Estimate System. Insider trades are from the Thomson Insider Trading Database. Numbers in parentheses are *t*-statistics.

	Abnormal shorting flows (past five-day − previous 20-day)	Abnormal shorting flows (past five-day − previous 60-day)
Panel A: Earnings news		
D10	0.55	0.52
	(1.92)	(1.88)
D1	0.19	0.07
	(0.67)	(0.27)
D1–D10	−0.36	−0.45
	(−0.89)	(−1.16)
Panel B: Analyst recommendation changes		
Upgrade	0.04	−0.16
	(0.39)	(−1.63)
Downgrade	−0.10	0.03
	(−0.99)	(0.34)
Downgrade–upgrade	−0.14	0.19
	(−1.03)	(1.46)
Panel C: Insider trading		
Large insider buys	0.13	−0.37
	(0.37)	(−0.91)
Large insider sells	0.41	−0.14
	(1.83)	(−0.54)
Sells–buys	0.28	0.23
	(0.65)	(0.49)

sort all sample stocks into decile portfolios based on the most recent SUE. Those in the lowest SUE decile are classified as bad news, and those in the highest SUE decile are classified as good news. We then compare the abnormal shorting activities prior to good and bad earnings news.

We again measure abnormal shorting flows in two ways: past-week shorting flows minus past-month shorting flows and past-week shorting flows minus past-quarter shorting flows. Regardless of which abnormal shorting flow measure used, we find no evidence that the shorting flows are abnormally high during the five days prior to the announcement of negative earnings news. In fact, the abnormal shorting flows are higher prior to good earnings news than prior to bad earnings news, although the difference is statistically insignificant.

Panel B presents the results for analyst recommendations. We define analyst downgrades as bad news and analyst upgrades as good news. Because both the content and the timing of analyst recommendation changes are unknown to the public, this analysis represents a more stringent test of whether short sellers possess private information. Similar to our results for earnings news, we find no evidence that short selling activities are concentrated just prior to analyst downgrades. Indeed, the abnormal shorting flows before analyst downgrades are not significantly different from the abnormal shorting flows before analyst upgrades.

In Panel C, we use large insider sales as a proxy for negative private information.[11] Prior literature has presented substantial evidence that insider trades are informed (e.g., Lakonishok and Lee, 2001). If short sellers are informed and have access to the same information possessed by insiders, we would expect short selling to be abnormally high prior to large insider sales. We fail to find such evidence—the abnormal shorting flows before large insider sales are not reliably different from the abnormal shorting flows before large insider buys. Overall, our results indicate no evidence that shorting flows are abnormally high over the five days prior to negative earnings surprises, analyst downgrades, and large insider sales. This finding is inconsistent with the hypothesis that short sellers derive their predictive power mainly from private information about future news.

Prior studies find mixed evidence on whether short sellers possess private information about impending negative news events. Christophe et al. (2004) find that short-selling activity is abnormally high prior to disappointing earnings announcements, suggesting that short sellers have access to nonpublic material information. Christophe et al. (2010) show that short selling activity is concentrated

[11] We calculate insider trading ratio as the share volume divided by total shares outstanding and define large insider sales (buys) as those insider trades in the top five percentiles of this ratio.

in periods preceding analyst downgrades.[12] However, not all studies find that short sellers are informed about upcoming news announcements. Daske et al. (2005) find that short sales are not concentrated prior to bad news. Engelberg et al. (2012) show that the highest shorting volume occurs during the day of public news announcements rather than the preceding ten trading days. They conclude that short sellers' returns are related to their ability to interpret, rather than predict, public news announcements. Similarly, Drake et al. (2015) show that short sellers are not able to anticipate restatement announcements.

Our finding that abnormal shorting flows do not anticipate impending bad news is consistent with Daske et al. (2005), Engelberg et al. (2012), and Drake et al. (2015) but inconsistent with Christophe et al. (2004) and Christophe et al. (2010). Our results are different from the last two studies in part because our sample period is more recent. In particular, short-sale volume has increased considerably in recent years, accounting for 36% of the total trading volume during our sample period. This significant growth might have diluted the potential private information possessed by some short sellers. Moreover, the public disclosure of daily short-sale volume in recent years may have discouraged short sellers from trading on short-term private information, as suggested by the theory of DeMarzo et al. (1998) and SEC (2014). Finally, the regulatory environment regarding the release of nonpublic information has become stricter post-Regulation FD (Fair Disclosure) and the Dodd-Frank Act. Such regulatory change may have reduced the informational advantage of short sellers, limiting their ability to obtain privileged information. As a result, short sellers, at least as a group, rely more heavily on public information as opposed to private information to derive their informational advantage during our sample period.

3.7. Anomalies

The evidence we have presented so far suggests that the predictability of shorting flows is more likely to arise from long-term public information. To further investigate the nature of the information that short sellers exploit, we examine 20 prominent anomaly variables that the previous literature has found to be significantly related to the cross-section of stock returns, including momentum, asset growth, and gross profitability. These 20 anomaly variables, which are derived from financial statements, analysts' forecasts, and market price and trading data, contain valuable information about the fundamentals of the underlying stocks. If short sellers are sophisticated investors who understand the return predictability associated with these signals, we would expect short sellers to engage in the short arbitrage of these anomalies.

3.7.1. Sample of anomalies

To compile a list of stock return anomalies, we start with the sample of Hou et al. (2015). We require that the anomaly variable be continuous (not an indicator variable) and can be constructed using the CRSP, Compustat, and I/B/E/S data. Hou et al. (2015) group their sample of anomalies into several categories including "Momentum", "Value-versus-growth", "Investment", "Profitability", and "Trading frictions". To minimize duplication, we select a few important anomalies from each of the above categories. Our final sample includes 20 prominent anomalies such as momentum, asset growth, and gross profitability. The detailed list and definitions of these anomaly variables are contained in the Appendix. While not exhaustive, our sample contains most of the important anomaly variables known to predict the cross-section of stock returns.

When constructing anomaly variables, we include all NYSE, Amex, and Nasdaq common stocks (with a CRSP share code of 10 or 11). We exclude stocks with price lower than $5 or market capitalization ranked in the lowest NYSE decile. We use NYSE breakpoints to sort all sample stocks into deciles based on each anomaly variable. We examine the strategy that goes long on stocks in decile 10 and short those stocks in decile 1, with decile 10 (decile 1) containing the stocks that are expected to outperform (underperform) based on prior literature. Taking the momentum anomaly as an example, we sort past winners into decile 10 and past losers into decile 1. In contrast, for the asset growth anomaly, we sort low-asset growth stocks into decile 10 and high-asset growth stocks into decile 1 because prior studies (Cooper et al., 2008) have shown that low-asset growth firms earn significantly higher returns than high-asset growth firms.

We follow the previous literature in forming portfolios and determining the rebalancing frequency and holding period. Specifically, for anomalies constructed using annual Compustat data, we form portfolios at the end of each June in year t by using accounting data from the fiscal year ending in calendar year $t-1$ and hold the portfolio from July in year t to June in year $t+1$. For anomalies constructed using quarterly Compustat data, we form portfolios at the end of each quarter t by using accounting data from the fiscal quarter ending in calendar quarter $t-1$ and holding the portfolio over the calendar quarter $t+1$. To ensure that the quarterly accounting data are publicly available before the portfolio formation date, we also require that the quarterly earnings announcement date fall in calendar quarter $t-1$ or t. Finally, for anomalies constructed using monthly CRSP data, we form portfolios every month and hold the portfolio for one month.

3.7.2. Shorting flows and anomalies

To examine whether shorting flows are systematically related to anomaly variables, we use a portfolio approach. We start by forming shorting portfolios in the same way as in our previous analyses. That is, we sort sample stocks into quintile portfolios based on prior five days of average short volume ratio. For each shorting portfolio and for each anomaly, we then compute the average anomaly variable decile rank. We also compute the percentage of stocks that belong to the short leg, i.e., decile 1 in each anomaly.

As stated earlier, decile 10 of each anomaly represents the long leg, and decile 1 represents the short leg. If short sellers systematically trade on anomalies, we would

[12] Rees and Twedt (2018) also examine short selling around earnings announcements. Their evidence suggests that although short sellers are able, on average, to successfully anticipate earnings news, they continue to trade on the news after it is publicly revealed.

Table 8
Shorting flows and stock market anomalies.
This table presents the relation between anomaly decile ranks and shorting flow quintiles across 20 anomalies. Detailed descriptions of those anomalies are in the Appendix. Based on the value of each anomaly variable, we divide sample stocks into ten deciles (Decile 1 is the group with lowest future returns and Decile 10 is the group with the highest future returns). The short volume data are from Financial Industry Regulatory Authority, Inc. (FINRA). Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ with necessary data on short sales and anomaly variables from January 2010 to December 2015. On each trading day, we sort stocks into quintiles based on their past five-day average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The short volume ratio is short volume divided by total volume. Panel A reports the average decile rank for each anomaly variable. Panel B reports the percentage of stocks in the portfolio that belongs to Decile 1 (i.e., the short leg) of each anomaly. Numbers in parentheses are Newey-West *t*-statistics with 60 lags.

Anomaly	*Anomaly decile rank*			*Percent of stocks in anomaly short-leg*		
	Q5	Q1	Q5–Q1	Q5	Q1	Q5–Q1
52W	5.11	5.33	−0.22 (−4.18)	13.41	10.12	3.29 (5.53)
AG	5.05	5.39	−0.34 (−8.10)	16.08	12.64	3.44 (7.60)
B/M	4.84	5.46	−0.62 (−17.13)	14.82	10.05	4.78 (11.54)
CF/P	4.84	4.95	−0.11 (−2.22)	16.73	15.14	1.59 (3.95)
DISP	5.14	5.14	−0.00 (−0.09)	12.30	11.44	1.56 (2.85)
Distress	5.66	5.76	−0.10 (−1.78)	10.91	9.27	1.64 (5.09)
EAR	5.11	5.33	−0.22 (−4.18)	13.07	11.16	1.91 (5.24)
GP	5.94	6.07	−0.12 (−3.27)	10.79	7.30	3.48 (10.53)
I/A	5.28	5.87	−0.59 (−15.75)	11.61	7.42	4.19 (14.19)
Illiq	6.04	7.85	−1.80 (−17.49)	5.62	2.32	3.30 (6.41)
InvGrowth	5.23	5.46	−0.23 (−8.98)	13.54	12.22	1.32 (3.57)
IVOL	4.91	4.85	0.06 (0.93)	13.84	14.66	−0.82 (−1.19)
LongRev	5.36	5.70	−0.34 (−7.01)	13.58	11.1	2.48 (6.65)
MOM	5.20	5.89	−0.69 (−16.16)	13.08	9.20	3.88 (8.53)
NOA	5.78	5.85	−0.07 (−1.60)	10.99	10.80	0.19 (0.32)
ShortRev	5.29	5.81	−0.52 (−11.90)	12.87	11.55	1.33 (5.39)
Size	6.20	7.69	−1.49 (−13.99)	5.05	2.32	2.73 (5.87)
StockIssue	5.00	5.17	−0.17 (−2.87)	12.95	9.95	3.00 (5.79)
TACC	5.33	5.34	−0.01 (−0.41)	14.46	13.81	0.65 (1.84)
TURN	5.04	6.91	−1.87 (−34.96)	13.79	3.49	10.30 (37.27)

expect the average decile anomaly rank for the high-shorting quintile to be significantly lower than the average decile anomaly rank for the low-shorting quintile. The left half of Table 8 presents the results for this analysis. We find that the average decile anomaly rank for high-shorting quintile is lower than that of low-shorting quintile for 19 out of 20 anomalies in our sample. Among the 19 anomalies, 15 anomalies exhibit statistically significant difference at the five percent level. For example, the average momentum decile rank for the high-shorting quintile portfolio is 5.2, while the average momentum decile rank for the low-shorting quintile portfolio is 5.89. The difference of 0.69 is highly statistically significant. This result suggests that short sellers exploit the momentum anomaly by avoiding stocks with high past returns.

The right half of Table 8 focuses on the short leg of each anomaly by presenting the percentage of stocks that belong to decile 1 of each anomaly. If short sellers systematically trade on anomalies, we would expect the high-shorting quintile to contain a higher percentage of short-leg stocks than the low-shorting quintile. We find evidence consistent with this hypothesis. The percentage of short-leg stocks is higher in the high-shorting quintile among 19 out of 20 anomalies, and significantly higher in 17 anomalies. For example, 13.08% of the stocks in high-shorting quintile belong to the lowest momentum decile, while 9.2% of the stocks in the low-shorting quintile belong to the same decile. We find these numbers to be economically meaningful, albeit not overwhelming. The modest differences reported in Table 8 are perhaps due to the fact that short sales now account for over one third of the total trading volume. It seems unreasonable to expect such a large proportion of the trading to exhibit a substantial tilt in either direction.

Overall, consistent with short sellers trading on anomalies, daily shorting flows are significantly higher among stocks that are in the short-leg of the anomalies, e.g., past losers, high asset growth, and low profitability stocks. The anomaly variables considered in this study are persistent. This explains why long-term shorting flows predict future returns as well as (or even better than) short-term shorting flows. Moreover, prior literature has shown that the informational content of anomaly variables (e.g., asset growth) is typically impounded into prices with significant delays, which explains why shorting flows predict both short- and long-run returns. Overall, short sellers' trading on anomalies provides a unifying explanation for our previous findings that shorting flows' predictability decays slowly and lasts for a year, long-term shorting flows predict returns as well as (or even better than) short-term shorting flows, and abnormal short-term shorting flows do not predict future returns.

3.8. Evidence from 2005 to 2007

We have shown that shorting flows predict negative future stock returns during 2010–2015. Moreover, this predictability is longer term than what previous studies have found. To provide a more explicit comparison with previous data, we repeat all of our analyses by using the

Table 9
Daily shorting flows and future stock returns: 2005–2007.
This table presents the equal- and value-weighted average daily returns of quintile portfolios sorted based on past five-day short volume ratios. We obtain the short-sale data through Regulation SHO. Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2005 to June 2007. On each trading day, we sort stocks into quintiles based on their past five-day average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The short volume ratio is short volume divided by total volume from TAQ. Panel A reports the average return for day 1 after portfolio formation. Panel B reports the average return from Day 2 to Day 21 after portfolio formation. We estimate one-, three-, and four-factor alphas based on the market model, the Fama and French (1996) model, and the Carhart (1997) model. Alphas are expressed in percent per day. Numbers in parentheses are *t*-statistics.

Shorting quintile	Equal weight			Value weight		
	One-factor α	Three-factor α	Four-factor α	One-factor α	Three-factor α	Four-factor α
Panel A: Day 1						
1 (lowest)	0.034	0.034	0.034	0.030	0.032	0.031
	(3.05)	(3.73)	(3.74)	(2.92)	(3.14)	(3.08)
2	0.014	0.020	0.020	0.012	0.013	0.013
	(1.30)	(3.08)	(3.05)	(1.88)	(2.15)	(2.08)
3	0.000	0.007	0.007	−0.007	−0.005	−0.005
	(0.02)	(1.26)	(1.29)	(−1.38)	(−0.90)	(−0.85)
4	−0.011	−0.008	−0.007	−0.016	−0.018	−0.016
	(−0.96)	(−1.41)	(−1.35)	(−2.51)	(−2.86)	(−2.83)
5 (highest)	−0.007	−0.005	−0.006	−0.012	−0.016	−0.015
	(−0.68)	(−0.98)	(−1.02)	(−1.64)	(−2.46)	(−2.40)
5–1	−0.041	−0.039	−0.039	−0.042	−0.048	−0.047
	(−3.92)	(−3.86)	(−3.91)	(−2.98)	(−3.60)	(−3.55)
Panel B: Day 2 to Day 21						
1 (lowest)	0.022	0.023	0.022	0.015	0.017	0.017
	(2.12)	(2.81)	(2.80)	(2.05)	(2.30)	(2.46)
2	0.011	0.016	0.016	0.003	0.005	0.005
	(1.05)	(2.84)	(2.86)	(0.66)	(1.11)	(1.18)
3	0.001	0.007	0.007	−0.004	−0.002	−0.002
	(0.14)	(1.60)	(1.60)	(−1.11)	(−0.51)	(−0.54)
4	−0.006	−0.001	−0.001	−0.010	−0.011	−0.012
	(−0.51)	(−0.30)	(−0.33)	(−1.99)	(−2.46)	(−2.78)
5 (highest)	−0.009	−0.007	−0.007	−0.009	−0.012	−0.012
	(−0.89)	(−1.55)	(−1.53)	(−1.35)	(−2.16)	(−2.30)
5–1	−0.031	−0.030	−0.029	−0.024	−0.028	−0.029
	(−3.50)	(−3.57)	(−3.56)	(−2.05)	(−2.70)	(−2.93)

2005–2007 RegSHO data. Regulation SHO was adopted by the SEC in June 2004 to establish new rules regarding short sales and to evaluate the effectiveness of price test restrictions on short sales. At the same time, the SEC mandated that all self-regulatory organizations (SROs) make transaction-level short-sale data publicly available. We collect short-sale transactions from all SROs including Amex, ARCA, Boston, Chicago, NASD, Nasdaq, NSX, NYSE, and PHLX for the period from January 2005 to June 2007. Because short sales for a given stock can occur at multiple venues, we aggregate the data across all exchanges for each stock on each day.

The RegSHO data for 2005–2007 represent an ideal data set for comparison with the FINRA data for 2010–2015. Both data sets are comprehensive in their coverage of sample stocks and trading venues. Also, both sample periods are characterized by a generally rising market and have similar levels of market volatility. In performing our analyses for the RegSHO sample, we use the same methodologies as those for the FINRA sample and, for ease of comparison, we tabulate the results using identical table format.

3.8.1. Baseline results

Table 9 presents the baseline results for the RegSHO sample. We find that heavily shorted stocks (those with high past five-day shorting flows) significantly underperform lightly shorted stocks. This result is qualitatively the same as that for the FINRA sample (Table 2), and holds whether we use one-, three-, or four-factor alphas, whether we use equal-weighted or value-weighted returns, and whether we examine a holding period of one day or 20 days (after skipping one day). The magnitude of the underperformance is also similar between the RegSHO sample and the FINRA sample. For example, looking at value-weighted three-factor alphas in Table 9, we find that heavily shorted stocks underperform lightly shorted stocks by 4.8 basis points (*t*-statistic = 3.6) on day 1, and by 2.8 basis points per day (*t*-statistic = 2.7) from day 2 to day 21. In comparison, the underperformance for the FINRA sample is 4.0 basis points (*t*-statistic = 4.18) on day 1, and by 2.4 basis points per day (*t*-statistic = 4.03) from day 2 to day 21. The only significant difference exists for the equal-weighted alphas for day 2 to day 21 (Panel B). Here, the underperformance is greater in the FINRA sample than in the RegSHO sample. Overall, we find that shorting flows are informed about near-term stock returns during 2005–2007, consistent with Boehmer et al. (2008) and Diether et al. (2009).

3.8.2. Long-run performance

Table 10 presents the long-run performance results for 2005–2007. Here, we find little evidence of long-run

Table 10
Daily shorting flows and long-run future stock returns: 2005–2007.

This table presents the cumulative equal- and value-weighted Fama and French three-factor risk-adjusted returns of the portfolios sorted based on past five-day short volume ratios. We obtain the short-sale data through Regulation SHO. Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2005 to June 2007. On each trading day, we sort stocks into quintiles based on their past five-day average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The holding period varies from Day 22 to Day 60, Day 61 to Day 90, Day 91 to Day 120, and to Day 121 to Day 252 after portfolio formation. The short volume ratio is short volume divided by total volume from TAQ. Returns are in percent. Numbers in parentheses are Newey-West adjusted *t*-statistics.

Shorting quintile	Day (22, 60)	Day (61, 90)	Day (91, 120)	Day (121, 252)
Panel A: Equal weight				
1 (lowest)	0.08	0.33	0.07	−1.46
	(0.16)	(0.91)	(0.16)	(−0.64)
2	0.07	0.16	0.04	−0.96
	(0.24)	(0.78)	(0.17)	(−0.80)
3	0.10	0.13	−0.01	−0.75
	(0.40)	(0.79)	(−0.03)	(−0.95)
4	0.06	0.08	−0.02	−0.79
	(0.25)	(0.47)	(−0.12)	(−1.35)
5 (highest)	−0.08	−0.07	−0.19	−1.03
	(−0.41)	(−0.41)	(−1.09)	(−2.65)
5–1	−0.16	−0.40	−0.25	0.43
	(−0.37)	(−1.10)	(−0.73)	(0.22)
Panel B: Value weight				
1 (lowest)	0.27	0.14	0.11	−0.74
	(1.57)	(0.76)	(0.52)	(−0.87)
2	−0.24	−0.34	−0.18	−0.33
	(−1.47)	(−2.91)	(−1.59)	(−0.71)
3	−0.27	−0.09	−0.06	−0.13
	(−1.33)	(−0.65)	(−0.44)	(−0.20)
4	−0.16	0.01	−0.08	−0.15
	(−1.16)	(0.05)	(−0.57)	(−0.18)
5 (highest)	−0.20	−0.15	−0.22	−0.92
	(−1.18)	(−1.01)	(−1.87)	(−1.63)
5–1	−0.47	−0.29	−0.33	−0.18
	(−2.15)	(−1.22)	(−1.49)	(−0.15)

underperformance by heavily shorted stocks. When we examine equal-weighted returns, none of the performance difference is statistically significant (Panel A). When we examine value-weighted returns, only one of the performance difference is statistically significant, which occurs during day 22 to day 60, immediately after our baseline holding period of day 1 to day 21 (Panel B). For all holding periods after day 60, there is no evidence that heavily-shorted stocks underperform lightly-shorted stocks. These results are in stark contrast to those for the 2010–2015 period. In particular, we show in Table 4 that underperformance of heavily-shorted stocks is significant for each holding period after day 21 and lasts for a year. Our results suggest that the predictability of shorting flows is much longer term during 2010–2015 than 2005–2007.

3.8.3. Long-term shorting flows

Table 11 examines the predictive ability of long-term shorting flows during 2005–2007. Here, we find only weak evidence that long-term shorting flows predict negative stock returns. The magnitude of the underperformance is around 2 basis points per day with *t*-statistics of around 2. This evidence is much weaker than the predictive ability of short-term shorting flows reported in Table 9 and substantially weaker than the predictive ability of long-term shorting flows during 2010–2015 (reported in Table 5).

3.8.4. Abnormal shorting flows

Table 12 examines the predictive ability of abnormal short-term shorting flows (i.e., the difference between short-term shorting flows and long-term shorting flows) for future stock returns. We find strong evidence that abnormal short-term shorting flows is a significant and negative predictor of future stock returns. This result is contrary to our previous finding that abnormal short-term shorting flows are uninformative about future stock returns during 2010–2015 (Table 6) but is consistent with our results in Table 9 and Table 11 that short-term shorting flows are more informative about future stock returns than long-term shorting flows during 2005–2007.

3.8.5. News

In Table 13, we examine whether shorting flows are abnormally high during the five trading days preceding bad news. As in Table 7, we define bad news as negative earnings announcements, analyst recommendation downgrades, and large insider sales. We do not find abnormally higher shorting flows before negative earnings announcements and large insider sales. However, we find evidence that short sellers can anticipate analyst downgrades during 2005–2007. These results are more supportive of the private information hypothesis than those for 2010–2015.

Table 11
Long-term shorting flows and future stock returns: 2005–2007.
This table presents the daily equal- and value-weighted average future 20-day returns of the portfolios based on two long-term past shorting flow measures: the average short volume ratio from Day −25 to Day −6 (Panel A), and the average short volume ratio from Day −65 to Day −6 (Panel B). We obtain the short-sale data through Regulation SHO. Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2005 to June 2007. On each trading day, we sort stocks into quintiles based on their past average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The holding period is from Day 2 to Day 21 after portfolio formation. The short volume ratio is short volume divided by total volume from TAQ. We estimate one-, three-, and four-factor alphas based on the market model, the Fama and French (1996) model, and the Carhart (1997) model. Alphas are expressed in percent per day. Numbers in parentheses are t-statistics.

Shorting quintile	Equal weight			Value weight		
	One-factor α	Three-factor α	Four-factor α	One-factor α	Three-factor α	Four-factor α
Panel A: $SHORT_{t-25,\ t-6}$						
1 (lowest)	0.016	0.016	0.016	0.013	0.015	0.015
	(1.50)	(1.93)	(1.92)	(1.62)	(1.79)	(1.92)
2	0.012	0.017	0.017	0.000	0.002	0.003
	(1.13)	(2.74)	(2.75)	(0.07)	(0.47)	(0.49)
3	0.005	0.010	0.010	−0.009	−0.006	−0.006
	(0.41)	(2.08)	(2.08)	(−1.89)	(−1.31)	(−1.31)
4	−0.003	0.002	0.002	−0.004	−0.005	−0.005
	(−0.23)	(0.35)	(0.34)	(−0.66)	(−0.82)	(−0.95)
5 (highest)	−0.010	−0.008	−0.008	−0.006	−0.009	−0.010
	(−0.88)	(−1.54)	(−1.53)	(−0.73)	(−1.39)	(−1.49)
5–1	−0.025	−0.024	−0.024	−0.019	−0.024	−0.024
	(−2.44)	(−2.46)	(−2.45)	(−1.40)	(−1.94)	(−2.13)
Panel B: $SHORT_{t-65,\ t-6}$						
1 (lowest)	0.016	0.017	0.016	0.016	0.018	0.018
	(1.51)	(1.88)	(1.87)	(1.76)	(1.99)	(2.12)
2	0.013	0.018	0.018	−0.008	−0.006	−0.006
	(1.18)	(2.64)	(2.65)	(−1.26)	(−0.98)	(−0.97)
3	0.001	0.007	0.007	−0.007	−0.002	−0.002
	(0.11)	(1.33)	(1.33)	(−1.22)	(−0.47)	(−0.46)
4	−0.001	0.003	0.003	0.000	−0.002	−0.002
	(−0.13)	(0.61)	(0.60)	(−0.08)	(−0.30)	(−0.38)
5 (highest)	−0.009	−0.007	−0.007	−0.005	−0.008	−0.008
	(−0.78)	(−1.37)	(−1.37)	(−0.57)	(−1.13)	(−1.25)
5–1	−0.025	−0.024	−0.024	−0.021	−0.026	−0.026
	(−2.23)	(−2.25)	(−2.25)	(−1.41)	(−1.95)	(−2.16)

3.8.6. Anomalies

Finally, in Table 14 we examine the extent to which short sellers trade on prominent anomalies during 2005–2007. We examine the same set of 20 anomalies as in Table 8. If short sellers exploit anomalies, then the average anomaly decile rank for Q5 would be significantly lower than that for Q1. We should also find that the percentage of stocks in the anomaly's short leg is significantly higher for Q5 than that for Q1. Our results indicate that short sellers trade on some anomalies. However, this evidence is significantly weaker and less uniform than that for the 2010–2015 sample period.

3.8.7. Summary

In summary, we find that shorting flows are significant negative predictors of future stock returns during 2005–2007. However, this predictability is much shorter term than 2010–2015. We argue that the combination of a substantial increase in short-sale volume, the public disclosure of daily short-sale data, and a stricter regulatory environment regarding the release of nonpublic information in more recent time periods explains why short sellers now rely more heavily on long-term public information when making shorting decisions.

3.9. Additional analyses

In this section, we provide a number of robustness and additional analyses. To conserve space, we report the results of these analyses in the Internet Appendix.

3.9.1. Alternative asset pricing models

We repeat our main analyses by using the Fama and French (2015) five-factor model and the Hou et al. (2015) q-factor model to evaluate the performance of shorting flow portfolios. Tables A1 through A5 in the Internet Appendix contain the detailed results for the FINRA sample (2010–2015), and Tables E1 through E5 contain the detailed results for the RegSHO sample (2005–2007). Overall, we find that our results are extremely robust. In fact, some of the results are more significant and more consistent under these alternative asset pricing models. This finding helps mitigate a concern that the predictability of shorting flows is due to systematic risk.

3.9.2. Weekly rebalancing

In our main analyses, we form quintile shorting portfolios each day. To examine whether our results are robust to less frequent portfolio rebalancing, which incurs lower trading costs, we repeat our analysis by forming portfolios once a week instead of every day. The holding periods are

Table 12
Abnormal short-term shorting flows and future stock returns: 2005–2007.
This table presents the daily equal- and value-weighted average future 20-day returns of the portfolios based abnormal short-term shorting flows. We measure abnormal short-term shorting flows in two ways. The first (Panel A) is the difference between past five-day average short volume ratio and the average short volume ratio from Day −25 to Day −6. The second (Panel B) is the difference between past five-day average short volume ratio and the average short volume ratio from Day −65 to Day −6. We obtain the short-sale data through Regulation SHO. Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2005 to June 2007. On each trading day, we sort stocks into quintiles based on abnormal shorting. Quintile 1 represents the portfolio with the lowest abnormal shorting, and Quintile 5 represents the portfolio with the highest abnormal shorting. The holding period is from Day 2 to Day 21 after portfolio formation. The short volume ratio is short volume divided by total volume from TAQ. We estimate one-, three-, and four-factor alphas based on the market model, the Fama and French (1996) model, and the Carhart (1997) model. Alphas are expressed in percent per day. Numbers in parentheses are t-statistics.

Shorting quintile	Equal weight			Value weight		
	One-factor α	Three-factor α	Four-factor α	One-factor α	Three-factor α	Four-factor α
Panel A: $SHORT_{t-5,\,t-1} - SHORT_{t-25,\,t-6}$						
1 (lowest)	0.014	0.016	0.016	0.009	0.008	0.008
	(1.42)	(2.89)	(2.90)	(1.94)	(1.87)	(1.87)
2	0.006	0.010	0.010	0.001	0.001	0.001
	(0.57)	(2.19)	(2.18)	(0.23)	(0.22)	(0.21)
3	0.002	0.007	0.007	0.000	0.002	0.002
	(0.21)	(1.43)	(1.43)	(0.06)	(0.95)	(0.95)
4	−0.002	0.002	0.002	−0.003	−0.003	−0.003
	(−0.16)	(0.54)	(0.53)	(−1.12)	(−1.05)	(−1.05)
5 (highest)	0.000	0.003	0.003	−0.007	−0.008	−0.008
	(0.02)	(0.53)	(0.54)	(−1.51)	(−2.06)	(−2.06)
5–1	−0.013	−0.013	−0.013	−0.016	−0.017	−0.016
	(−3.61)	(−3.47)	(−3.46)	(−2.75)	(−2.78)	(−2.81)
Panel B: $SHORT_{t-5,\,t-1} - SHORT_{t-65,\,t-6}$						
1 (lowest)	0.017	0.019	0.019	0.010	0.009	0.009
	(1.81)	(3.36)	(3.35)	(1.75)	(1.71)	(1.70)
2	0.006	0.010	0.010	0.005	0.005	0.005
	(0.59)	(2.09)	(2.08)	(1.27)	(1.28)	(1.27)
3	0.001	0.006	0.006	0.002	0.003	0.003
	(0.12)	(1.26)	(1.25)	(0.55)	(1.17)	(1.18)
4	−0.002	0.002	0.002	−0.008	−0.007	−0.007
	(−0.21)	(0.46)	(0.45)	(−2.23)	(−1.94)	(−1.94)
5 (highest)	−0.002	0.001	0.001	−0.012	−0.014	−0.014
	(−0.22)	(0.11)	(0.12)	(−2.35)	(−2.92)	(−2.91)
5–1	−0.019	−0.018	−0.018	−0.022	−0.023	−0.023
	(−4.09)	(−3.95)	(−3.94)	(−2.79)	(−2.95)	(−2.94)

unchanged; i.e., we skip a day and then hold the portfolios for 20 days. Table A6 in the Internet Appendix contains the results. We continue to find that heavily shorted stocks significantly underperform lightly shorted stocks. Moreover, we find that the results are nearly identical to those in Table 2, suggesting that weekly rebalancing generates about the same level of abnormal returns.

3.9.3. Sort on past one-day shorting

In our main analyses, we follow the methodology of Boehmer et al. (2008) and form quintile shorting portfolios based on prior five days of shorting flows. During 2010–2015, stock-level aggregate short-sale volume is published each day, so the short-sale volume for four of the past five days were already known to the public the day before. To focus on the predictive content of new information, we repeat our analysis by forming portfolios based on past one-day shorting flow. Table A7 in the Internet Appendix contains the results. Our holding periods are day 1 (Panel A) and day 2 through day 21 (Panel B). We continue to find that heavily shorted stocks significantly underperform lightly shorted stocks during both holding periods. The results are qualitatively similar to those in Table 2.

3.9.4. By exchange

Boehmer et al. (2008) use a proprietary data set provided by the NYSE and their analysis covers only NYSE stocks and short sale transactions executed in NYSE. In this section, we examine whether our results are robust across listing exchanges and trading venues. We examine three sub-samples: NYSE stocks, non-NYSE stocks, and NYSE stocks with only NYSE shorting volume. Tables B1 through B4, C1 through C4, and D1 through D4 in the Internet Appendix contain the results for these three sub-samples, respectively. Overall, we find our main results are broadly consistent across all three samples. In fact, the long-run performance results are the strongest in the third sub-sample, i.e., the same sample used by Boehmer et al. (2008), suggesting that the difference between our results and that of Boehmer et al. (2008) is not due to our differences in sample coverage.

3.9.5. Comparison of sample characteristics

We further examine whether the different results between our 2010–2015 FINRA sample and the 2005–2007 RegSHO sample are driven by differences in sample characteristics. We make two comparisons between these two samples. First, we compare the stock characteristics between the two samples. Second, we compare a number of

Table 13
Abnormal shorting flows prior to earnings surprises, analyst recommendation changes, and large insider trades: 2005–2007.

This table presents the abnormal short-term shorting flows prior to earnings news (Panel A), analyst recommendation changes (Panel B), and large insider trades (Panel C). We measure abnormal short-term shorting flows in two ways. The first is the difference between past five-day average short volume ratio and the average short volume ratio from Day −25 to Day −6. The second is the difference between past five-day average short volume ratio and the average short volume ratio from Day −65 to Day −6. We obtain the short-sale data through Regulation SHO. Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ from January 2005 to June 2007. The short volume ratio is short volume divided by total volume from TAQ. We measure earnings news by using the standardized unexpected earnings (SUE). Decile 10 represents good news and Decile 1 represents bad news. We scale the share volume of each insider trade by total shares outstanding and define large insider sale (purchase) as those ranked in the top five percentiles among all insider trades. Quarterly earnings and earnings announcement dates are from Compustat. Analyst recommendations are from Institutional Brokers' Estimate System. Insider trades are from the Thomson Insider Trading Database. Numbers in parentheses are *t*-statistics.

	Abnormal shorting flows (past five-day – previous 20-day)	Abnormal shorting flows (past five-day – previous 60-day)
Panel A: Earnings news		
D10	−0.19	−0.24
	(−0.68)	(−0.68)
D1	−0.18	−0.33
	(−0.62)	(−0.74)
D1–D10	0.01	−0.08
	(0.03)	(−0.26)
Panel B: Analyst recommendation changes		
Upgrade	0.00	−0.21
	(0.03)	(−1.55)
Downgrade	0.30	0.42
	(2.74)	(3.35)
Downgrade–upgrade	0.30	0.63
	(2.14)	(4.00)
Panel C: Insider trading		
Large insider buys	−0.44	−0.48
	(−1.63)	(−1.77)
Large insider sells	−0.27	−0.18
	(−1.48)	(−0.95)
Sells–buys	0.17	0.30
	(0.57)	(0.98)

Table 14
Shorting flows and stock market anomalies: 2005–2007.

This table presents the relation between anomaly decile ranks and shorting flow quintiles across 20 anomalies. Detailed descriptions of those anomalies are in the Appendix. Based on the value of each anomaly variable, we divide sample stocks into 10 deciles (Decile1 is the group with lowest future returns and Decile10 is the group with the highest future returns). We obtain the short-sale data through Regulation SHO. Our sample contains all common stocks (with a Center for Research in Security Prices share code of 10 or 11) listed on the NYSE, AMEX, and NASDAQ with necessary data on short sales and anomaly variables from January 2005 to June 2007. On each trading day, we sort stocks into quintiles based on their past five-day average short volume ratios. Quintile 1 represents the portfolio with the lowest short volume ratio, and Quintile 5 represents the portfolio with the highest short volume ratio. The short volume ratio is short volume divided by total volume from TAQ. Panel A reports the average decile rank for each anomaly variable. Panel B reports the percentage of stocks in the portfolio that belongs to Decile 1 of each anomaly. Numbers in parentheses are Newey-West *t*-statistics with 60 lags.

Anomaly	Anomaly decile ranks			Percent of stocks in anomaly short leg		
	Q5	Q1	Q5–Q1	Q5	Q1	Q5–Q1
52W	5.18	5.27	−0.09 (−0.43)	13.76	13.01	0.75 (0.41)
AG	5.01	5.49	−0.48 (−4.82)	14.55	11.24	3.31 (3.12)
B/M	5.16	4.97	0.19 (1.71)	13.29	13.83	−0.54 (−0.47)
CF/P	4.98	4.78	0.20 (0.99)	16.50	17.22	−0.72 (−0.29)
DISP	5.03	5.27	−0.24 (−1.51)	14.31	13.11	1.20 (0.81)
Distress	5.38	5.82	−0.44 (−7.90)	11.44	10.58	0.86 (1.06)
EAR	5.40	5.59	−0.19 (−3.58)	13.17	10.25	2.91 (3.60)
GP	5.66	5.94	−0.28 (−2.45)	11.60	8.76	2.84 (4.81)
I/A	5.13	5.91	−0.78 (−17.06)	12.81	7.07	5.74 (14.56)
Illiq	6.53	7.04	−0.51 (−1.88)	3.07	8.30	−5.22 (−4.39)
InvGrowth	5.07	5.77	−0.70 (−8.66)	13.71	11.50	2.21 (2.60)
IVOL	4.75	4.87	−0.12 (−0.67)	15.23	17.85	−2.62 (−2.07)
LongRev	5.29	6.02	−0.73 (−13.57)	14.74	10.61	4.12 (4.85)
MOM	5.26	5.75	−0.50 (−2.72)	14.01	9.84	4.17 (2.74)
NOA	5.39	6.09	−0.70 (−10.40)	12.81	8.70	4.11 (7.92)
ShortRev	5.22	5.82	−0.60 (−8.42)	13.76	11.57	2.18 (3.44)
Size	6.73	6.99	−0.26 (−0.81)	2.81	8.07	−5.26 (−4.20)
StockIssue	5.16	5.15	0.01 (0.12)	12.49	9.78	0.55 (0.96)
TACC	5.25	5.48	−0.23 (−4.41)	14.69	11.18	0.97 (0.69)
TURN	4.87	5.79	−0.92 (−7.90)	15.12	8.47	6.69 (7.16)

market-level variables between these two sample periods. Overall, we find no significant differences between the two samples except two characteristics. First, the short volume ratio is significantly higher during 2010–2015 than 2005–2007. Second, the short-term interest rate is lower during 2010–2015 than 2005–2007. Both of these differences are well-known. We present the results in Tables F1 and F2 of the Internet Appendix.

3.9.6. Short interest

Although our study focuses on the information content of daily shorting flows, most prior studies use monthly short interest data. In Table A8 of the Internet Appendix, we examine whether short interest contains similar predictive ability for future returns during our sample period. We form quintile portfolios based on two short interest ratios, one scaling short interest by shares outstanding and the other scaling short interest by trading volume. We find mixed evidence on whether short interest predicts future returns. When using equal-weighted portfolios, we find significant evidence that heavily shorted stocks underperform lightly shorted stocks. However, the results are insignificant when we examine value-weighted returns. This finding is consistent with prior studies (e.g., Asquith et al., 2005) and suggests that daily shorting flows contain incremental information relative to monthly short interest.

3.10. Discussions

One limitation of our data is that although we observe when short positions are established, we do not know when they are covered. Therefore, we do not know the exact duration of each short position. We follow prior studies and examine the performance of shorting flows over fixed investment horizons (e.g., 20 days). To the extent that short sellers are informed and that they are able to cover their short positions at more opportune times, our results represent a conservative estimate (i.e., lower bound) of the abnormal returns generated by short trades.

Another limitation of our data is that we observe only the aggregate short-sale volume across all short sellers. Although there are strong theoretical reasons to expect short sellers to be informed (Diamond and Verrecchia, 1987), there can be uninformed shorting. For example, traders may use short sales to hedge a long position in the same stock, to conduct convertible arbitrage, or to hedge their option positions. These short selling activities are not motivated by whether the stock itself is overvalued. Therefore, their presence in the data will work against us finding that stock-level aggregate shorting flows predict negative future returns.

Why does the market fail to incorporate the information contained in public shorting flows in a timely manner? One possibility is limits to arbitrage. We find, consistent with this argument, that the negative relation between shorting flows and future stock returns is more pronounced among small, illiquid, high IVOL, and low IO stocks. The slow reaction to the public shorting information may also be related to short-selling risk. Specifically, Engelberg et al. (2018) show that the dynamic risks associated with short selling result in significant limits to arbitrage. They find that stocks with more short selling risk have lower future returns, less price efficiency, and less short selling.

Another related explanation is transactions cost. We emphasize that all of the returns reported in our study are gross returns, i.e., they are before trading and shorting cost. Precise estimates of trading and shorting costs are difficult to obtain, but trading costs overall have fallen substantially in recent years with the advent of decimals and increased competition between liquidity providers. Moreover, we show that long-term shorting flows are more informative about future returns than short-term shorting flows. This suggests that frequent rebalancing of portfolios is not needed to capture the significant abnormal returns.

An alternate explanation for the slow market reaction to shorting information is risk-based, i.e., stocks with the greater shorting activities are less risky. Although we cannot completely rule out this possibility, we have shown that our results are robust to all the standard asset pricing models in the literature including one-, three-, four-, five-, and q-factor models. Moreover, to the extent that the 20 anomalies considered in our study are reflections of market inefficiency instead of compensation for risk, we argue that at least some of the predictive power of shorting flows are driven by mispricing rather than risk.

We aggregate shorting flows to the daily level and examine their predictive ability at horizons of one day or longer. As such, our paper cannot address the issue of intra-daily predictive ability of shorting flows. High frequency traders typically establish and close short positions within the day and are known to use recent order flow information to anticipate short-term price movements. Indeed, empirical academic studies (e.g., Hendershott et al., 2011) support the hypothesis that high-frequency or algorithmic trading promotes price efficiency and price discovery. In a related study, Aitken et al. (1998) show that real-time disclosure of short sales in Australia leads to immediate negative price impact intra-daily.

4. Conclusions

Prior literature presents strong evidence that daily shorting flows predict negative future stock returns. We show that this predictability remains highly significant during our sample period from 2010 to 2015, when daily short-sale volume data become publicly available in real time. This evidence suggests that the market is slow to impound public shorting information into prices and is inconsistent with the semi-strong form of market efficiency. The predictability of daily shorting flows persists for a year, much longer than previously documented. More importantly, long-term shorting flows are stronger predictors for future stock returns than short-term shorting flows. In fact, abnormal short-term shorting flows neither predict future returns, nor do they anticipate negative earnings news, analyst downgrades, or large insider sales. These results suggest that the continued predictability of daily shorting flows during 2010–2015 is primarily due to short sellers' trading on long-term information that is only gradually incorporated into prices. Consistent with this interpretation, we find that daily shorting flows are significantly higher

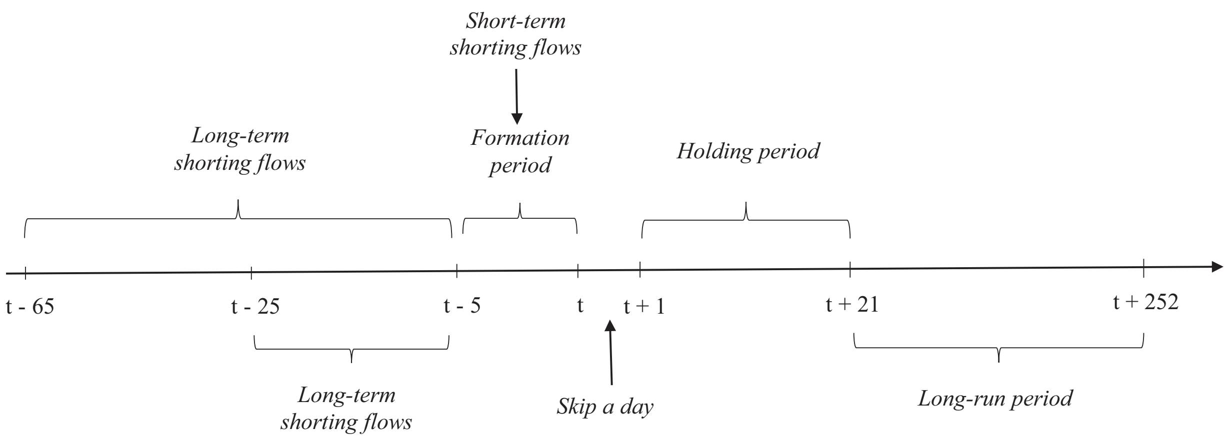

Fig. 1. Time line of portfolio formation and holding periods.

among stocks that are considered overvalued based on 20 prominent anomaly variables.

Our results suggest that short sellers as a group are well informed during our sample period and that the primary source of their informational advantage is long-term public information. A comparison with the RegSHO data confirms that the predictability is much shorter-term during 2005–2007. We argue that the combination of a substantial increase in short-sale volume, the public disclosure of daily short-sale volume data, and a stricter regulatory environment regarding the release of nonpublic information in more recent time periods explains why short sellers now rely more heavily on long-term, public information as opposed to short-term, private information when making shorting decisions (Fig. 1).

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Appendix A. List of anomalies

We include 20 prominent stock market anomalies in our tests. The table gives detailed descriptions of the anomaly variables and the papers in which the anomalies were first shown.

Term	Anomaly	Paper
52W	52-week high	George and Hwang (2004)
AG	Growth in total assets	Cooper et al. (2008)
B/M	Book-to-market equity	Rosenberg et al. (1985)
CF/P	Cash flow-to-price	Lakonishok et al. (1994)
DISP	Dispersion of analysts' earnings forecasts	Diether et al. (2002)
Distress	Financial distress	Campbell et al. (2008)
EAR	Abnormal returns around earnings announcements	Chan et al. (1996)
GP	Gross profitability-to-assets	Novy-Marx (2013)
I/A	Changes in property, plant, and equipment plus changes in inventory over total assets	Lyandres et al. (2008)
Illiq	Illiquidity	Amihud (2002)
InvGrowth	Inventory growth	Thomas and Zhang (2002)
IVOL	Idiosyncratic volatility	Ang et al. (2006)
LongRev	Long-term reversal	DeBondt and Thaler (1985)
MOM	Momentum (prior 11-month return)	Jegadeesh and Titman (1993)
NOA	Net operating assets	Hirshleifer et al. (2004)
ShortRev	Short-term reversal	Jegadeesh (1990)
Size	Market equity	Banz (1981)
StockIssue	Net stock issues	Pontiff and Woodgate (2008)
TACC	Total accrual	Sloan (1996)
TURN	Share turnover	Datar et al. (1998)

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