Do Daily Short Sales Forecast S&P 500 Sector Returns?

Leslie Boni and Mary Anne Majadillas

Abstract

We examine the data for S&P 500 firms for 2009 to 2012 to determine whether daily short selling, aggregated at the industry sector level, forecasts relative returns. Prior research documents short sellers as skilled fundamental analysts and information processors at the individual security level and in aggregate as forecasters of short-term market direction. Intriguingly, we find not only that sector-aggregated daily short sale information does not correctly forecast the short-term relative performance of industry sectors but rather that some contrarian strategies that are *short* the least shorted sectors and *long* the most shorted sectors are profitable on average.

I. Introduction

A growing body of academic research suggests short sellers detect and trade on short-term opportunities. Engelberg, Reed, and Ringgenberg (2012) examine daily short sales around Dow Jones News Service and Wall Street Journal stories. They find that the negative relation between short selling and future stock return is substantially larger around news days, particularly days with negative news. They conclude that "the evidence suggests that public news provides valuable trading opportunities for short sellers who are skilled information processors" (p. 260). Blau and Tew (2014) analyze daily short selling around class-action lawsuits and conclude "short activity surges in the days before the filing." Lynch, Nikolic, Yan, and Yu (2014) conclude that short sellers are informed at the market-wide level and document that aggregate daily short selling forecasts market-level returns for the following 5 to 20 trading days.

Our research question is whether daily short selling of individual firms -- aggregated by *industry sector* -- provides a valuable signal of sector future performance relative to other sectors. A finding that daily short sales forecast the relative returns of industry sectors could be of particular interest to portfolio managers. A commonly-used performance measure for equity portfolio management is attribution analysis, which compares the active return generated by the manager's sector allocation decisions with the active return generated from the selection of individual securities (see Held, 2009; Stewart, Piros, and Heisler, 2011 pp. 444-447; Reilly and Brown, 2012 pp. 988-989; and Bodie, Kane and Marcus, 2011 pp. 850-851).

Leslie Boni is an Associate Professor at the California State University, Monterey Bay. Mary Anne Majadillas is an Assistant Professor at the University of New Mexico. Contact E-mail: lboni@csumb.edu

The impact of sector weight decisions can dwarf the impact of individual stock selection for equity portfolio performance, but consistently forecasting relative sector performance is challenging. Reilly and Brown (2012, p.

560) write: “While there are impressive gains to be made in correctly timing the hottest (or the coldest) market sectors, a manager must be right substantially more than he or she is wrong. Because this is an extremely difficult thing to do consistently, many investors choose to interpret Exhibit 16.8 as ultimately extolling the virtue of asset and sector class diversification.”

Short sellers as skilled information processors might be particularly adept at interpreting and synthesizing information that disproportionately impacts sectors. Examples of such information are the impact of OPEC announcements for the Energy sector (Watts and Sjolin, 2014), FOMC announcements for the Utilities sector (Lydon, 2017), and regulatory announcements for the Financials and Health Care sectors (Moreno, 2014). Investment practitioners have a keen appreciation for the importance of understanding the information that drives sector returns. The equity research function at large sell-side and buy-side firms is typically organized by sector (Boni and Womack, 2006; Vardharaj and Fabozzi, 2007; and De Franco, Hope, and Laroque, 2013).

Even if short sellers do not attempt to forecast relative sector performance, their short selling aggregated across the individual firms they target might forecast sector relative performance. A growing body of research documents informed short selling at the individual security level. Among those that conclude short sellers are skilled analysts who synthesize publicly available information are Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Krishnamurthy, and Venkataraman (2006), Boehmer, Jones, and Zhang (2008), Karpoff and Lou (2010), and Engelberg, Reed, and Ringgenberg (2012). Other researchers provide evidence consistent with short sellers trading on private information in advance of announcements (Christophe, Ferri, and Angel, 2004; Christophe, Ferri, and Hsieh, 2010; and Blau and Tew, 2014). Regardless whether the information used by short sellers of individual securities is public or private, when aggregated by sector, this short selling could translate to a valuable signal of the sector’s future performance.

If aggregate daily short selling correctly forecasts relative sector performance, strategies that are long the least shorted sectors and short the most shorted sectors should earn abnormal positive returns. We analyze long-short sector strategies for a variety of daily short selling measures for the S&P 500 firms for September 2009 to December 2012. We examine our research question in the context of S&P 500 firms rather than all listed firms for several reasons. First, if aggregate daily short selling provides a reliable predictor, the sector selection strategies could be easily implemented using existing liquid sector ETFs (e.g., Select Sector SPDR ETFs). Second, Chan, Lakonishok, and Swaminathan (2007) find that the comovement of returns that results from industry-sector effects is more pronounced for large firms than for small firms.

Refuting our conjecture that aggregate daily short selling correctly forecasts future relative performance, our empirical findings are that *none* of the long-short strategies based on the various aggregate daily short selling measures earns average returns that are significantly positive. When means of returns are significantly different from zero, they are *negative.* Further analysis shows that contrarian strategies using some of the daily short selling measures may be profitable. These strategies are *short* the least shorted sectors and *long* the most shorted sectors. Separate probit analysis confirms that aggregate daily short selling does not correctly forecast future sector performance. Overall, our results are consistent with a hypothesis that the bulk of daily short selling is liquidity provision by market makers, high-frequency trading, or hedging, rather than the positioning of short sellers who correctly place bets on short-term overvaluation.

Our paper contributes to recent research that examines whether short selling, aggregated across individual short sellers, provides valuable investment signals. As in the previously referenced research by Lynch, Nikolic, Yan, and Yu (2014), we examine aggregated *daily short selling* data for U.S. stocks. While Lynch, et al (2014) focus on whether short selling predicts overall market direction, we focus on the relative performance of sectors. Our findings that contrarian strategies might be profitable extend the research of Mohamad, Jaafar, and Goddard (2016). They examine a measure of *daily short interest* for ETFs traded on the London Stock Exchange. They find a positive association between increases in short interest and abnormal returns. They note that their measure of daily short interest is not observable by researchers for ETFs in the U.S.

Our findings are in contrast to those of other researchers who examine *monthly short interest* data and longer-horizon investment strategies. Huszar, Tan, and Zhang (2017) examine monthly short interest data for U.S.-listed firms aggregated across a 24-industry group classification and find strategies that short heavily shorted industries might be profitable over a one-month to six-month horizon. Rapach, Ringgenberg, and Zhou (2016) conclude that short sellers correctly predict future cash flows and, as a result, aggregate short interest is the best predictor of overall market performance in the next one, three, six, and twelve months.

The remainder of the paper is organized as follows. Section 2 discusses the data, sector variables, and descriptive statistics. Section 3 provides a probit analysis of whether aggregate daily short selling forecasts sector winners or losers. Section 4 reports results for the weekly long-short portfolios constructed from short sale daily data. Section 5 discusses results for long-short portfolios formed at a daily frequency. Section 6 concludes.

II. Data, sector variables, and descriptive statistics

A. Data

As of September 2009, many of the U.S. self-regulatory organizations (SROs) provided free internet access to their daily total short sale share volume for each security after the close of trading.[1] Thus, since September 2009, daily short sale data have been available to the public for their use in next-day trading decisions. We download short sale data from each SRO's website for September 1, 2009 through December 31, 2012 and retain data for S&P 500 firms. Daily stock returns, share prices and volume, and shares outstanding are from CRSP.

[1] SRO short sale data web links were reached through http://www.sec.gov/answers/shortsalevolume.htm. The SROs during the sample period are BATS Exchange, Inc.; Direct Edge Holdings, LLC; Financial Industry Regulatory Authority, Inc.; International Securities Exchange, LLC; NASDAQ Stock Market LLC; NASDAQ OMX BX, Inc.; National Stock Exchange, Inc.; New York Stock Exchange LLC; NYSE Amex LLC; and NYSE Arca, Inc. We purchased NYSE's data. NYSE was the only SRO that charged for their short sale data during the sample period.

We partition the S&P 500 firms by 2-digit Global Industry Classification Standard (GICS) classifications from Compustat (see Bhoraj, Lee, and Oler, 2003; Chan, Lakonishok, and Swaminthan, 2007). The GICS 2-digit classification consists of ten sectors: Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunications, and Utilities. Just two firms, AT&T and Verizon, dominate the Telecommunication sector. We include the Telecommunications sector firms in the Information Technology sector. This is consistent with how State Street Bank and Trust Company partitioned the S&P 500 firms during the time period to create nine very liquid Select Sector SPDR ETFs, which could be used in aggregate to replicate the S&P 500 index.

B. Sector variables

Our focus is whether daily short sale data for one week can be used to forecast sector relative return performance the following week. Although it might be possible for traders to aggregate short sale information after the close in time to implement trading strategies the following day prior to the close, our weekly trading strategies avoid possible day of the week or weekend effects documented for short selling by Christophe, Ferri, and Angel (2009), Blau, Van Ness, and Van Ness (2009), and Lynch, Nikolic, Yan, and Yu (2014).

We calculate weekly sector variables as follows. For each stock, we calculate two short sale measures each day. The first is the percentage of share volume shorted (sv_{it}), which is the number of shares shorted divided by the stock's share volume that day. The second measure is the percentage of outstanding shares shorted (ss_{it}), which is the number of shares shorted divided by the number of shares outstanding. Weekly measures are obtained for each weekday. For example consider a position initiated at closing prices for Friday, August 20, 2010, and liquidated on the close Friday, August 27, 2010.

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Friday, 8/13 Thursday, 8/19 Friday, 8/20 Friday, 8/27

We define week *w* as Friday's close August 20 through Friday's close August 27. The holding period return is Ret_w. The period for short sale measures (used for trading decisions for week *w*) is defined as week *w-1*, which consists of the trading days of Friday, August 13, through Thursday, August 19, in the example. The weekly *w-1* short sale measures for each firm are the averages for the daily measures (sv_{it} and ss_{it}) for the days in week *w-1*. The weekly short sale measures for each sector (SV_{w-1} and SS_{w-1}) are the market capitalization weighted averages for the firms in the sector, where the market capitalization for each firm is the average of its daily market capitalizations for week *w-1*. In other words, short sale daily measures are averaged for Friday through the following Thursday to create the decision variable for forecasting returns for the next day Friday's close through the Friday close of the following week. Similarly, for positions initiated and liquidated on Monday closes, the average of daily short sale information for the prior week's Monday through Friday is used, etc. Because we want to analyze not only levels of short sale measures but also changes in levels week over week, we calculate the percentage change in the short sale variables (ΔSV_{w-1} andΔSS_{w-1}) as the percentage change in the weekly short sale measure for week *w-1* relative to week *w-2*.

For ease of exposition, throughout the paper, we define "best" and "worst" short selling from the standpoint of the buy-and-hold investor, who likely prefers little or no short seller activity. Thus, a sector is the "best" ("worst") in terms of the short selling level measures (SV_{w-1} and SS_{w-1}) if it has the lowest (highest) value that week compared with the other sectors. For the percentage change measures (ΔSV_{w-1} and ΔSS_{w-1}), "best" means the sector has the largest percentage decrease in short selling level relative to the level the prior week (or has the least increase if all sectors' changes are positive). "Worst" means the sector has the largest increase (or has the least decrease if all sectors' changes are negative).

C. Descriptive statistics

Table I Panel A reports descriptive statistics for each of the nine sectors. There are 166 weeks in the sample period. *Weight* is the sector's weight in the S&P 500.

The mean of weekly return (*Ret*) for the sample period is slightly positive for each of the sectors, ranging from the low for Financials at 0.116% to the high of 0.385% for Consumer Discretionary. The means of short sale levels as a percentage of share volume (*SV*) range from 44.9% (Health Care) to 48.5% (Consumer Discretionary). These levels are higher for the sample period relative to levels reported by researchers using the 2005 to 2007 transaction-level data. For example, Diether, Lee, and Werner (2009) report a mean of 23.4% for large NYSE stocks and 37.8% for large Nasdaq stocks for January 3, 2005 to December 30, 2005. Lynch, et al (2014) report a mean of 24.2% for the value-weighted average across common stocks for January 3, 2005 to June 29, 2007. The means of short sales as a percentage of shares outstanding (*SS*) are also higher, ranging from 0.251% (Consumer Staples) to 0.658% (Materials) as compared with a mean of 0.182% for the value-weighted average across common stocks reported by Lynch, et al (2014). Changes from week to week are greater in magnitude for shorted shares as a percentage of shares outstanding (ΔSS) than as a percentage of daily share volume (ΔSV).

Correlations among the variables are reported in Panel B of Table I. Holding period returns for week w (Ret_w) are negatively correlated with week $w\text{-}1$ holding period returns (Ret_{w-1}) and the week $w\text{-}1$ percentage change in outstanding shares shorted (ΔSS_{w-1}). They are weakly positively correlated with the week $w\text{-}1$ level of share volume shorted (SV_{w-1}). Contemporaneous levels of the two short selling measures (SV_{w-1} and SS_{w-1}) are positively correlated as are percentage changes (ΔSV_{w-1} and ΔSS_{w-1}).

Panel C of Table I reports the average number of firms per sector.[2] The 3 largest -- Consumer Discretionary, Financials, and Information Technology (including Telecommunication) -- average about 80 firms each and together account for almost half of the firms in the S&P 500. The smallest 2 sectors -- Materials and Utilities -- average about 30 firms each.

Chan, Lakonishok, and Swaminathan (2007) find the finer partition of the GICS 6-digit ("industry") classification is even better for explaining industry effects of return comovement than is our GICS 2-digit "sector" partition. Academic research highlights the value of forecasting future winners or losers at the industry level (e.g., Huszar, Tan, and Zhang, 2017;

[2] During the sample period, some firms were removed and others added to the S&P 500 index. We report the average number of firms for the Friday-basis weekly sector variables.

Kacperczyk, Sialm, and Zheng, 2005; Busse and Tong, 2012; Jame and Tong, 2014). It is reasonable to ask whether our analysis would be of more value if performed at the industry, rather than the sector, level.

To address this question, the last columns of Table I Panel C report the number of industries per sector and minimum and maximum number of firms by industry if we use the GICS 6-digit (“industry) classifications for the S&P 500 firms. Using the GICS 6-digit classifications greatly reduces the number of firms. Some of the industries in 6 of the sectors have just one firm. We conclude the finer GICS 6-digit classification is too fine for our analysis of S&P 500 firms.

Table I. Descriptive statistics

Panel A: Weekly sector variables

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Utilities
N	166	166	166	166	166	166	166	166	166
Weight	0.105	0.119	0.114	0.149	0.116	0.104	0.224	0.035	0.035
	(0.005)	(0.005)	(0.007)	(0.008)	(0.005)	(0.003)	(0.006)	(0.001)	(0.002)
Ret (%)	0.385	0.282	0.223	0.116	0.270	0.270	0.264	0.215	0.227
	(2.708)	(1.507)	(3.321)	(3.341)	(1.898)	(2.958)	(2.604)	(3.455)	(1.890)
SV	0.485	0.453	0.479	0.484	0.449	0.474	0.467	0.480	0.478
	(0.033)	(0.036)	(0.033)	(0.034)	(0.035)	(0.035)	(0.032)	(0.033)	(0.036)
ΔSV (%)	0.895	0.950	0.512	0.553	0.865	0.798	0.619	0.978	1.270
	(3.872)	(5.404)	(5.494)	(4.657)	(4.379)	(4.433)	(4.253)	(5.366)	(5.568)
SS (%)	0.583	0.251	0.397	0.502	0.323	0.370	0.517	0.658	0.332
	(0.115)	(0.054)	(0.097)	(0.151)	(0.075)	(0.095)	(0.112)	(0.184)	(0.083)
ΔSS (%)	6.205	5.274	4.134	5.522	6.229	5.283	5.519	5.194	5.999
	(18.495)	(18.696)	(18.686)	(22.109)	(19.728)	(19.708)	(19.187)	(19.019)	(21.002)

Panel A reports means (and standard deviations in parentheses) for sector variables used for Friday-initiated portfolios with one-week holding periods.

Panel B: Pearson correlation coefficients

	Ret_w		Ret_{w-1}		SV_{w-1}		ΔSV_{w-1}		SS_{w-1}	
Ret_{w-1}	-0.083	***								
SV_{w-1}	0.043	*	-0.032							
ΔSV_{w-1}	0.000		-0.129	***	0.302	***				
SS_{w-1}	-0.032		-0.105	***	0.330	***	0.043	*		
ΔSS_{w-1}	-0.067	***	-0.235	***	-0.028		0.149	***	0.197	***

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

Panel C: Company and industry statistics

	Average number of companies per sector	Industries per sector	Average number of companies per industry: Minimum	Average number of companies per industry: Maximum
Consumer Discretionary	79.9	12	1.0	18.0
Consumer Staples	41.0	6	2.4	14.4
Energy	40.6	2	11.1	29.5
Financials	80.0	8	1.0	21.5
Health Care	51.6	6	1.0	15.8
Industrials	59.7	12	1.0	14.2
Information Technology	81.3	10	1.0	17.9
Materials	30.5	5	2.5	14.1
Utilities	33.2	4	1.0	15.0
All	500	65	1.0	29.5

III. Probit analysis of forecasting winners and losers

We first analyze whether short selling can be used to forecast the sectors that will have the best return (the "winner") or worst return (the "loser"). If the probability of being the sector with the best return is equal for all sectors, each of the nine sectors should have the best return in Panel A of Table II (column Ret_w) for 11.1% of the weeks. Using a chi-square test, we reject the null hypothesis at the 1% level that sectors are equally likely to have the best return. Similarly, the hypothesis of equal probability for having the best short selling is rejected for each of the four short selling measures at the 1% level. Chi-square tests also reject the null of equal probability of being the worst sector in terms of the return (Ret_w) and four short selling measures at the 1% level (Panel B).

Table II. Sector rankings by returns and short sale measures

Panel A: Best sectors	Ret_w		SV_{w-1}		ΔSV_{w-1}		SS_{w-1}		ΔSS_{w-1}	
	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior	% of Weeks	Pr | Prior
Consumer Discretionary	9.0%	0.067	0.0%	-	3.1%	0.208	0.0%	-	6.2%	-
Consumer Staples	10.8%	0.168	34.3%	0.582	9.9%	-	98.8%	0.988	5.0%	0.130
Energy	15.7%	0.232	7.8%	0.387	18.6%	0.069	0.0%	-	14.9%	0.043
Financials	13.9%	-	1.2%	-	11.2%	0.058	0.0%	-	16.1%	0.080
Health Care	9.0%	0.134	44.0%	0.593	9.3%	-	0.0%	-	11.2%	-
Industrials	4.2%	-	1.2%	-	7.5%	-	0.0%	-	11.8%	0.055
Information Technology	6.6%	-	4.2%	-	7.5%	-	0.0%	-	9.3%	-
Materials	16.9%	0.036	3.0%	-	16.1%	0.120	0.0%	-	9.3%	-
Utilities	13.9%	0.131	4.2%	-	16.8%	-	1.2%	-	16.1%	0.040
All	11.1%	0.097	11.1%	0.491	11.1%	0.045	11.1%	0.976	11.1%	0.039
Memo: Best 3 Sectors	33.3%	0.321	33.3%	0.683	33.3%	0.224	33.3%	0.838	33.3%	0.234
Panel B: Worst sectors										
Consumer Discretionary	4.8%	-	16.9%	0.323	6.8%	0.094	22.3%	0.653	9.9%	-
Consumer Staples	10.2%	0.118	0.0%	-	14.9%	0.087	0.0%	-	8.1%	0.080
Energy	13.9%	0.131	24.1%	0.503	13.7%	0.189	0.0%	-	7.5%	-
Financials	18.7%	0.227	19.9%	0.213	9.9%	-	3.6%	0.168	19.3%	0.067
Health Care	6.0%	-	0.0%	-	9.3%	-	0.0%	-	11.8%	-
Industrials	6.6%	0.091	3.6%	-	8.1%	-	0.0%	-	10.6%	-
Information Technology	9.0%	0.201	0.6%	-	7.5%	-	6.6%	0.549	7.5%	-
Materials	13.3%	0.183	17.5%	0.243	9.9%	0.065	67.5%	0.880	9.9%	0.065
Utilities	17.5%	0.208	17.5%	0.208	19.9%	0.097	0.0%	-	15.5%	0.083
All	11.1%	0.158	11.1%	0.297	11.1%	0.071	11.1%	0.782	11.1%	0.039
Memo: Worst 3 Sectors	33.3%	0.319	33.3%	0.640	33.3%	0.224	33.3%	0.899	33.3%	0.241

The columns labeled "Pr|Prior" report for return (Ret_w) and each of the four short selling measures the probability the sector will be the best sector (Panel A) or worst sector (Panel B) conditional on being the best sector (Panel A) or worst sector (Panel B) for the prior week. If being the best (worst) one week has no impact on the probability of being the best (worst) the next week, "Pr|Prior" should be one in nine (11.1%). For example, Panel B reports, for all sectors combined, the probability of having the worst return (Ret_w), conditional on having the worst return the prior week, is 15.8%. This suggests using the prior week's relative return performance may help forecast losers.

To analyze whether short selling, possibly in combination with the prior week's relative return performance, can be used to forecast winners or losers, we estimate the following probit model specifications:

$$WINNER_{j,w} = \beta_0 + \beta_1 Ret_{j,w-1} + \beta_2 WINNER_{j,w-1} + \beta_3 LOSER_{j,w-1} + \beta_4 ShortMeasure\_rank_{j,w-1} + \varepsilon_{j,w} \quad (1)$$

$$LOSER_{j,w} = \beta_0 + \beta_1 Ret_{j,w-1} + \beta_2 WINNER_{j,w-1} + \beta_3 LOSER_{j,w-1} + \beta_4 ShortMeasure\_rank_{j,w-1} + \varepsilon_{j,w} \quad (2)$$

In model 1, the dependent variable *WINNER* equals 1 if sector *j* is the winner (the sector with the best return) in week *w*, and equals 0 otherwise. The independent variables include sector *j*'s return in the prior week ($Ret_{j,w-1}$). Including $Ret_{j,w-1}$ allows us to test whether having a positive return in the prior week increases the probability of being a winner, in which case we expect a positive estimate for β_1. The dummy variable $WINNER_{j,w-1}$ takes the value 1 if sector *j* is the winner in the prior week. A positive estimate for β_2 would be consistent with sector "repeat winners". Model 1 also includes a dummy variable $LOSER_{j,w-1}$, which takes the value 1 if sector *j* is the loser in the prior week. We include this dummy variable to allow for the possibility that sector relative volatility drives extreme winner and loser rankings. If the probability of winning and losing is related to extreme short-term volatility and sectors oscillate from having the best to worst relative returns from one week to the next, then the estimate for β_3 should be positive. For each of the 4 short selling measures, we determine $ShortMeasure\_rank_{j,w-1}$, which is the sector's rank from 1 (best) to 9 (worst) relative to the other sectors. If less short selling (relative to the other sectors) forecasts better relative returns, we expect β_4 to be negative for model 1.

For model 2, the dependent variable *LOSER* equals 1 if sector *j* is the loser (the sector with the worst return) in week *w*, and equals 0 otherwise. Consistent with the reasoning for model 1, $Ret_{j,w-1}$ allows us to test whether having a negative return in the prior week increases the probability of being a loser, in which case we expect a negative estimate for β_1. If the probability of winning and losing is related to extreme short-term volatility, the estimate for β_2 should be positive. A positive estimate for β_3 would be consistent with sector "repeat losers". If more short selling (relative to other sectors) forecasts worse relative returns, we expect β_4 to be positive for model 2.

We estimate the models for each of the four short selling measures. We cluster standard errors by sector. To avoid overlapping observations and to allow for possible day-of-the-week anomalies, we estimate the models separately for each of the "weekday-of-initiation" measures. For example, Table III reports the results for the estimates for the weekly measures for positions initiated on Fridays.

Panel A of Table III reports the results for the probit regressions for the probability of being the winner. The pseudo R^2 is extremely small for each regression. With the exception of the estimates for the coefficients for the short selling measure rankings for SV_{w-1} and ΔSV_{w-1}, none of the estimates are statistically significant at conventional levels. Interestingly, the significant estimates for SV_{w-1} and ΔSV_{w-1} are positive, which is the opposite of the sign we expect if less short selling forecasts better relative returns. Having lower short selling relative to the other sectors, measured as either the level or percentage change of share volume shorted (SV_{w-1}), *reduces* the probability of being the next week's winner. Evaluated at the mean of $Ret_{j,w-}$

$_1$ and values of 0 for the $WINNER_{w-1}$ and $LOSER_{w-1}$ dummy variables, being the sector with the least (versus the most) short selling reduces the probability of being the winner by 3.7% for the SV_{w-1} measure and by 5.8% for the ΔSV_{w-1} measure.

Table III. Probit regressions of forecasting sector winners and losers

Panel A: Probability that sector will be the winner

	(1)	(2)	(3)	(4)
Intercept	-1.3497 ***	-1.4232 ***	-1.3044 ***	-1.2293 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Ret_{w-1}	-0.6599	-1.0047	-0.5380	-0.7011
	(0.751)	(0.618)	(0.802)	(0.749)
$WINNER_{w-1}$	-0.0756	-0.0574	-0.0711	-0.0497
	(0.716)	(0.783)	(0.733)	(0.817)
$LOSER_{w-1}$	0.1028	0.1022	0.0970	0.0902
	(0.410)	(0.411)	(0.408)	(0.475)
SV_rank_{w-1}	0.0249 **			
	(0.037)			
ΔSV_rank_{w-1}		0.0386 ***		
		(0.000)		
SS_rank_{w-1}			0.0161	
			(0.413)	
ΔSS_rank_{w-1}				0.0010
				(0.955)
Pseudo R^2	0.0033	0.0061	0.0021	0.0010
N	1,493	1,449	1,493	1,449

Panel B: Probability that sector will be the loser

	(1)	(2)	(3)	(4)
Intercept	-1.3046 ***	-1.1755 ***	-1.2177 ***	-1.0279 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Ret_{w-1}	0.5571	0.6995	0.6449	0.6295
	(0.778)	(0.708)	(0.741)	(0.739)
$WINNER_{w-1}$	0.1144	0.0693	0.1192	0.0888
	(0.505)	(0.714)	(0.490)	(0.641)
$LOSER_{w-1}$	0.2676 ***	0.2517 ***	0.2726 ***	0.2764 ***
	(0.001)	(0.004)	(0.001)	(0.002)
SV_rank_{w-1}	0.0071			
	(0.759)			
ΔSV_rank_{w-1}		-0.0175		
		(0.243)		
SS_rank_{w-1}			-0.0106	
			(0.677)	
ΔSS_rank_{w-1}				-0.0496 ***
				(0.000)
Pseudo R^2	0.0045	0.0047	0.0047	0.0121
N	1,493	1,449	1,493	1,449

P-values in parentheses. ***, **, and * statistical significance at 1%, 5%, and 10%, respectively.

The results for the probit regressions for the probability of being the loser are reported in Panel B of Table III. Being the loser for the prior week provides help in forecasting whether the sector will be a "repeat loser". As in model 1, the pseudo R^2 is again extremely small for each regression, however. The only other estimate that is significantly different from 0 is the estimate for the percentage change in outstanding shares shorted measure (ΔSS_{w-1}). Similar to what we observed for forecasting the probability of winning, the estimate has the opposite sign we expect if short selling forecasts relative returns. The estimate is negative, meaning that a higher percentage change in outstanding shares shorted reduces the probability of being the next week's loser.

Untabulated results of the probit regressions for the weekly measures for positions initiated on the other days of the week tell a consistent story as to the potential for using sector short selling to forecast winners and losers. Results are available by request. Summarizing the results of the analysis reported in this section, we find no evidence that sector-aggregated short sale information correctly forecasts sector winners or losers.

IV. Long-short portfolio analysis

A. Long-short strategies

We next analyze whether long-short portfolio strategies based on the aggregate daily short selling measures are profitable. We concluded in the previous section that the short selling measures did little to help us correctly forecast *which* sectors would have the best or worst returns. And interestingly, estimates for the short measures, when significant, had the opposite of the sign we expected. It is possible, however, that the sectors with more short selling have lower *returns* the following week *on average* than the sectors with less short selling.

To analyze this, we construct weekly long-short portfolios that are long the firms of the least shorted sector and are short the firms of the most shorted sector. We examine the long-short strategy separately for each of the weekly short sale measures (SV_{w-1}, ΔSV_{w-1}, SS_{w-1}, and ΔSS_{w-1}) and for each weekday of initiation. We also analyze portfolios long the firms of the three sectors with the least short sales and short the firms of the three sectors with the most short sales, with the three sectors equally weighted in the long and short portfolios. For comparison, we report returns for two additional long-short portfolio strategies. The first is the strategy that assumes perfect foresight. In other words, it assumes we know the best and worst performers one week in advance. The returns from this strategy are reported to indicate the maximum return from picking sector winners and losers (excluding transaction costs). The other strategy is a return momentum-based strategy, which uses sector rankings based on week *w-1* holding period returns (Ret_{w-1}).

Returns for the long-short portfolios are reported in Table IV. Average weekly returns for the long-short strategies which are long the best sector and short the worst sector are reported in Panel A. The first column provides the results for the strategy that assumes perfect foresight. Labeled Ret_w, it shows there are substantial opportunities for gains from picking the best and worst sectors. The mean of weekly returns ranges from a low of 3.60% for weekly portfolios formed on Wednesdays to a high of 3.82% for portfolios formed on Fridays. In stark contrast, the means of returns for the long-short strategy based on forming portfolios using their returns for the prior week (Ret_{w-1}) are sometimes negative, and never significantly different from zero.

For the short selling strategies, the means of the returns are rarely significantly different from zero; but when they are significant, they are negative. Specifically, the means of returns are negative and significant for the portfolios formed on Tuesdays and Fridays using the change in short volume measure. The means of returns are also negative and significant for the portfolios formed on Mondays and Fridays using the change in short shares outstanding measure.

Table IV. Long-short portfolio returns

Panel A: Weekly returns for "best sector - worst sector" strategies

	Ret_w	Ret_{w-1}	SV_{w-1}	ΔSV_{w-1}	SS_{w-1}	ΔSS_{w-1}
Mondays	3.72% ***	0.27%	-0.06%	-0.12%	-0.16%	-0.28% *
Tuesdays	3.71% ***	-0.05%	0.03%	-0.32% **	-0.01%	0.00%
Wednesdays	3.60% ***	-0.11%	-0.06%	-0.13%	-0.08%	0.04%
Thursdays	3.63% ***	-0.10%	-0.05%	-0.19%	-0.17%	-0.26%
Fridays	3.82% ***	0.14%	0.00%	-0.31% *	-0.22%	-0.29% *

Panel B: Weekly returns for "best 3 sectors - worst 3 sectors" strategies

	Ret_w	Ret_{w-1}	SV_{w-1}	ΔSV_{w-1}	SS_{w-1}	ΔSS_{w-1}
Mondays	2.51% ***	0.08%	-0.15%	-0.09%	-0.16% *	0.03%
Tuesdays	2.45% ***	-0.07%	-0.06%	-0.21% **	0.00%	-0.03%
Wednesdays	2.46% ***	-0.09%	-0.06%	-0.18% **	-0.01%	-0.10%
Thursdays	2.51% ***	-0.08%	-0.07%	-0.30% ***	-0.06%	-0.11%
Fridays	2.59% ***	-0.03%	-0.10%	-0.26% ***	-0.07%	-0.22% **

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

Panel B reports the returns for the long-short portfolios formed using the best 3 sectors and the worst 3 sectors. Returns are similar to those we observed in Panel A. The means of weekly returns for picking the best 3 and worst 3 sectors with perfect foresight are large, ranging from a low of 2.45% for the Tuesday portfolios to a high of 2.59% for those formed on Fridays. Returns based on returns for the prior week are never significantly different from zero. For the short selling strategies, when the means of the weekly returns are significantly different from zero, they are negative.

In summary, we conclude that none of the sector-aggregated short sale measures result in long-short portfolios that earn mean returns that are significantly positive.

B. Contrarian strategies

The results in the last section suggest that contrarian weekly strategies, which are *short* the least shorted sectors and *long* the most shorted sectors, might be profitable on average, prior to transaction costs, for some of the short selling measures. In this section, we examine the risk characteristics of these contrarian strategies and whether they are stable over time. We focus on the portfolios formed on Fridays and use the two *change* in short selling measures.

Annualized return, annualized volatility, and Sharpe ratio for the sample period are shown in the upper panel of Table V. For all four of the contrarian strategies, Sharpe ratios (prior to transaction costs and assuming 0.25% for the annualized risk-free rate) are almost 0.9 or higher. Although both of the "Best 3 – Worst 3" strategies have annualized returns that are less than either of "Best – Worst" strategies, the "Best 3 – Worst 3" strategies have less volatility and better Sharpe ratios.

Table V. Return performance and risk of contrarian strategies

Panel A: Annualized performance of weekly strategies

	Annualized Return	Annualized Volatility	Sharpe Ratio
Best - Worst Strategies			
Change in Short Shares Outstanding	14.88%	16.46%	0.889
Change in Short Volume	14.06%	15.32%	0.901
Best 3 - Worst 3 Strategies			
Change in Short Shares Outstanding	13.15%	9.26%	1.393
Change in Short Volume	10.86%	8.63%	1.229

Panel B: Fama-French three risk factor model plus Carhart [1997] momentum

	Alpha	Excess Market	Size (SMB)	Value (HML)	Momentum (WML)	Annualized Alpha
Best - Worst Strategies						
Change in Short Shares Outstanding	0.0035 *	-0.116	0.054	-0.149	-0.079	18.18%
Change in Short Volume	0.0031 *	-0.096	0.063	0.031	0.070	16.04%
Best 3 - Worst 3 Strategies						
Change in Short Shares Outstanding	0.0029 ***	-0.043	0.006	-0.039	-0.101	14.95%
Change in Short Volume	0.0022 **	-0.002	0.004	-0.067	-0.011	11.19%

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

The lower panel in Table V reports the coefficient estimates for the Fama-French three risk factor model plus Carhart (1997) momentum. All four strategies have alpha (weekly basis) returns that are significant at the 10% level, ranging from 0.22% to 0.35%. None of the three Fama-French risk factors or momentum coefficient load at the 10% level.

Table VI reports the means of weekly returns for each contrarian strategy by year and overall for the entire sample period. Means are positive each year with the exception of the change in short volume strategies for 2010. Standard deviations of weekly returns are reported under the means in parentheses. Returns are sufficiently volatile to prevent weekly returns from being statistically different from zero at the 10% level for most years.

While the results presented here are intriguing, it is worth emphasizing that the results are for portfolios formed on Friday closes only and for the *changes* in short selling strategies only. Our results suffer from hindsight bias in that we intentionally selected the strategies and formation day which we expected to have the greatest potential given the results of their non-contrarian counterparts. Nor have we been able to obtain and analyze daily short sale data and strategy performance for the period after December 31, 2012.

Table VI. Contrarian strategy performance by calendar year.

	Sept. - Dec. 2009		2010	2011	2012		Sept. 2009 - Dec. 2012	
Best - Worst Strategies								
Change in Short Shares Outstanding	0.57%		0.45%	0.22%	0.21%		0.31%	*
	(1.84%)		(2.63%)	(2.64%)	(1.61%)		(2.28%)	
Change in Short Volume	0.37%		-0.07%	0.45%	0.46%	**	0.29%	*
	(2.17%)		(1.97%)	(2.71%)	(1.51%)		(2.12%)	
Best 3 - Worst 3 Strategies								
Change in Short Shares Outstanding	0.20%		0.31%	0.44%	0.07%		0.26%	***
	(1.11%)		(1.29%)	(1.48%)	(1.10%)		(1.28%)	
Change in Short Volume	0.57%	**	-0.01%	0.19%	0.37%	***	0.22%	**
	(0.84%)		(1.07%)	(1.57%)	(0.93%)		(1.20%)	

This table reports means of weekly returns with standard deviations in parentheses.
***, **, and * are statistical significance of 2-sided *t*-tests of means at 1%, 5%, and 10%, respectively.

V. Long-short portfolios formed daily

We check whether daily short selling forecasts sector performance when long-short portfolios are formed daily. We initiate the long-short positions on the close each day using short sale data from the prior day. The portfolio positions are liquidated on the close of the following trading day. We form portfolios for each of the four short sale measures.

Similar to what we document for the weekly portfolios, the potential gain from placing daily long-short portfolio "sector bets" with perfect foresight is high. Before transaction costs, the means of the daily raw returns and four-factor adjusted returns for the "perfect foresight" portfolios are 1.7% for the Best – Worst portfolios and 1.1% for the Best 3 – Worst 3 portfolios. However, the means of the raw returns and four-factor adjusted returns from the daily long-short portfolios using the short sale measures are not significantly different from 0.

VI. Concluding remarks

We use daily short selling data from September 2009 through December 2012 to examine whether short selling, aggregated at the sector level, forecasts the relative performance of sectors for S&P 500 firms. Using a probit analysis, we find that more heavily shorted sectors do *not* underperform the following week. The means of returns of long-short portfolios constructed each week – short the sector(s) with most short selling (aggregated across firms) and long the sector(s) with least short selling -- are not significantly different from 0 for most of the cases we examine. More interestingly, when the means of returns for the strategies are significantly different from 0, they are negative suggesting a contrarian strategy could be profitable. Average returns for long-short portfolios formed daily are not significantly different from 0.

Our main contribution is to the area of recent research on whether short sellers are skilled at forecasting market direction overall and industry sector relative performance in particular. Lynch, Nikolic, Yan, and Yu (2014) conclude that aggregate daily short selling forecasts *market-*

level returns for the following 5 to 20 trading days. We document that aggregate short selling does not correctly forecast *relative sector performance*. Our findings offer an important extension to those of Mohamad, Jaafar, and Goddard (2016) who use a measure of daily short interest for ETFs traded on the London Stock Exchange. They find that aggregate short interest does not correctly forecast future ETF abnormal returns and suggest a contrarian strategy of taking long positions in heavily shorted ETFs. Our findings for short-term investment strategies are in contrast to those of Huszar, Tan, and Zhang (2017) and Rapach, Ringgenberg, and Zhou (2016) who examine *monthly short interest* data. They respectively conclude that short sellers correctly predict relative industry performance and overall market direction, thus providing valuable signals for longer-horizon investment strategies.

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