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ORIGINAL RESEARCH

The dynamic relation between options trading, short selling, and aggregate stock returns

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Abstract We examine the information contained in option trading and short selling using a dynamic VAR model. First, we address whether options and shorts are complements or substitutes. Contrary to existing event studies around option listing introductions, we show short selling and options trading are complements rather than substitutes. Second, we examine which group is relatively more informed. The results indicate that options traders are relatively more informed. Finally, we examine if options are redundant. Our results indicate that options markets are non-redundant.

Keywords Short selling · Options market · Informed traders · Time series analysis

JEL Classification G12 · G14 · G17

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1 Introduction

Relatively little is known about the relation between short selling and options trading. Even less is known about the dynamic relation between the two. In this paper, we investigate the dynamic time-series relation between aggregate monthly short interest, option open interest, the ratio of option volume to stock volume, and equity returns for S&P 500 firms.

We focus on three issues:

1. Are short selling and options trading substitutes or complements?
2. Does aggregate options trading add to market completeness (i.e., is the options market non-redundant)?
3. Who is relatively more informed between short sellers and options traders?

The results of our dynamic analysis, whose methodology is derived from Granger (1969) and Sims (1972), provide new insights into these questions. Specifically, our results indicate that short selling and options trading are complements and not substitutes, options are non-redundant assets (i.e., there is information in options not contemporaneously incorporated into the underlying stocks), and options traders are relatively more informed than short sellers.

The first issue we investigate, whether short selling and options trading are complements or substitutes, has been addressed frequently in the literature. However, a consensus has not been reached and previous methodologies may not be reliable. The assumption of substitutability is commonly made in the extant literature that examines the effect of short sale constraints on the (over)valuation of stocks. Some argue, following Miller (1977), that in an environment of heterogeneous beliefs about a stock's value, optimists will purchase the stock and pessimists will short the stock. If short sale constraints are present, however, the optimists will have a larger impact on the stock's price and thus cause overvaluation. Diamond and Verrecchia (1987) propose that unexpected short selling is indicative of bad news, which is empirically confirmed by Aitken et al. (1998). However, there are many studies that find no evidence of substitution between short selling and options trading (e.g. Battalio and Schultz 2006, 2011; Grundy et al. 2012; Blau and Brough 2015). Prior literature in this area focuses on static tests such as an event study methodology to examine new option exchange listings and their impact on the equities market.[1] Importantly, the dynamic tests in this paper avoid the problems of endogeneity faced by previous studies to examine the relations between the substitutability between short sales and option open interest over time. Specifically, short selling is related to the decision to list on an options exchange (Blau and Brough 2013). Thus, previous event studies linking option listing decisions and subsequent stock returns suffer from endogeneity. Our empirical approach avoids such issues in two ways. First, we focus on stocks that already have options traded on them which is an improvement over focusing on the endogenous decision to list on an options exchange. Second, our dynamic tests explicitly establish the lead/lag relation between options and shorts.

The second issue we consider is the information provided by the options market.[2] Specifically, if short selling and options are not found to be substitutes (i.e., informed traders are not leaving the equities market to participate in the options market), it is not apparent that options markets add information about the equities market. Again, the

[1] We discuss this literature in detail in Sect. 2.

[2] Hasbrouck (1991a, b) uses dynamic VAR models to establish the information linkage between stock trades, prices, and bid-ask spreads.

evidence in the literature is mixed on this subject. While studies such as Stephan and Whaley (1990), Chan et al. (1993), Kluger and Wyatt (1995), Chan et al. (2002), He et al. (2010) and Muravyev et al. (2013) find no evidence of options markets adding to equity market completeness, a plethora of other studies (discussed at length below) find otherwise.

Related to the issue of redundancy is the third issue addressed in our paper. Specifically, we ask whether short sellers or options traders are relatively more informed. Extant literature makes a good case for both short sellers and options traders being sophisticated investors and superior processors of information. Our methodology can help discern which group of traders, short sellers or options traders, have better predictive power over equity returns.

The results indicate that aggregate option open interest follows aggregate returns and short interest. This suggests that, in aggregate, options open interest contains little information about future equity returns, and the options market is redundant. However, we find that the Roll et al. (2010) ratio of dollar option volume to dollar stock volume, which includes important price information about options that open interest alone omits, leads both aggregate returns and aggregate short selling. Thus, when considering both option prices and activity, we find that the options market is informed and non-redundant. Finally, we find that once past returns are controlled for, aggregate short trading is unable to add predictive ability for future returns. Collectively, our results suggest that short sellers are not particularly informed in aggregate while options traders are relatively more informed. This result is counter to Blau and Wade (2013), who find that short trading is four times more informed than options markets. We note that we find similar results with respect to the lack of information in option markets when we focus on the same proxy for option market activity as Blau and Wade (2013). However, when we use the Roll et al. (2010) ratio of dollar option volume to dollar stock volume measure, we find the opposite result that option markets are more informed. In general, the results in our paper are sensitive to the use of levels or first-differences of variables and to the inclusion of price information for options. The conclusions discussed above relate to tests that appropriately control for nonstationarity and cointegration. Differences in results are discussed in the robustness section.

The remainder of the article is organized as follows. Section 2 discusses the related literature. Section 3 discusses the data and variables. Section 4 discusses how to investigate whether options and short trading are complements or substitutes and how to test whether short traders and options traders are informed traders based on potential information asymmetry between these traders and other investors. Section 5 presents the empirical findings. Section 6 concludes the paper.

2 Literature review

The literature provides empirical evidence (e.g. Sorescu 2000; Danielsen and Sorescu 2001) which shows post-1980 stock prices decline upon option introduction. This seems to confirm a relaxation of short sale constraints and suggests pessimistic investors substitute options for shorting (by either buying puts or writing calls). Consistent with Miller's predictions, Phillips (2011) finds options alleviate a majority of pricing inefficiencies between constrained and unconstrained stocks, but only with respect to negative news (i.e., no efficiency gains are present with positive news). Accordingly, analyses such as Boehme et al. (2006) explicitly use stock option status as an indicator of lessened short sale constraints.

However, not all studies are consistent in revealing shorting and options as substitutes. For example, Lakonishok et al. (2007) document non-market maker investors are net writers of options, with the majority of their open interest in call options. Evans et al. (2009) provide evidence that options market makers, as counterparties to investors who are synthetically shorting, hedge their inherently long position by shorting the stock. Additionally, Battalio and Schultz (2006) and Blau and Brough (2015) find no evidence of substitutability between short sales and bearish option trades. These findings place short selling and options markets not as substitutes, but rather as complements: higher options trading activity would coincide with higher short selling, but, according to hedging argument, not necessarily vice versa.

Given that Chan et al. (2002) find informed traders operate in the equities market, and Danielsen et al. (2007) find the market quality of the underlying security improves prior to option listing, an argument can be made that increased short selling, in conjunction with option activity, drives the results of Sorescu (2000) and Danielsen and Sorescu (2001). Additionally, D'Avolio (2002), Asquith et al. (2005) and Boehmer et al. (2008) demonstrate that the vast majority of stocks are not short-sale constrained, thus there is little motivation for the short seller to migrate to options. Battalio and Schultz (2011) and Grundy et al. (2012) notice volume and liquidity decreased for options on stocks that fell under the US SEC's September 2008 short sale ban and show it is difficult to switch strategies from short selling to options trading when market makers are uncertain about their ability to hedge.

The literature is also inconclusive on the topic of options market redundancy. Some evidence suggests that the options market is redundant. For example, Stephan and Whaley (1990) and Chan et al. (1993) use intraday data to show that the equities market leads the options market and that the options market does not add additional information. Chan et al. (2002), Mayhew and Mihov (2005) and Muravyev et al. (2013) reach similar conclusions. However, other studies show that the options market is non-redundant. Black (1975), Manaster and Rendleman (1982), Figlewski and Webb (1993), Buraschi and Jackwerth (2001), Vanden (2004, 2006) and Buraschi and Jiltsov (2006) (among others) either theoretically show or empirically demonstrate the options market is non-redundant to the equities market, and contains information not contemporaneously incorporated in the stock market.[3] Similarly, Pan and Poteshman (2006) provide evidence that initiated put volume relative to call volume has explanatory power over future stock returns, and that options traders possess nonpublic information. Roll et al. (2010) and Johnson and So (2012) demonstrate the return predictability of option to stock trading volume ratio which also suggests options traders are informed. Consequently, the options market is thought to provide price discovery that is incremental to that of the underlying equities market.

With respect to relative informativeness, Diamond and Verrecchia (1987) explain investors would not short sell for liquidity reasons since the proceeds from the short sale are not available for use by the investors. Therefore, the majority of short sales should be informed and not noise trades. Supporting this assertion, Dechow et al. (2001) demonstrate short sellers trade against firms whose fundamental ratios do not support their price. Drake et al. (2011) find similar evidence of short sellers trading based on firm fundamentals, and show short sellers outperform analysts in this regard.[4] Diether et al. (2009b) also find short sellers are contrarian with respect to momentum, selling stock after past positive returns.

[3] Black (1975) reasons that the natural leverage provided by options provides an attractive arena for informed traders to act on their information. Additionally, Easley et al. (1998) show that there can exist a pooling equilibrium where informed traders will prefer to execute information in the options market. Additionally, Ang et al. (2006), DeLisle et al. (2011) and Chang et al. (2013) find evidence that the implied volatility and skewness from options prices are priced in the cross-section of stock returns as state variables.

[4] Many other studies find short sellers profit from accounting-based information, establishing them as advanced information processors, including Desai et al. (2006).

Consistent with these findings, Jain et al. (2012) find stocks are more heavily shorted prior to negative returns, not after.

Several studies, such as Asquith and Meulbroek (1995), Wu et al. (1996), Jayaraman et al. (2001), Desai et al. (2002), Boehmer et al. (2008), Diether et al. (2009b) and French et al. (2012) show an inverse relation between short sales and future returns, indicating short sellers can predict stock returns. Furthermore, Safieddine and Wilhelm (1996), Christophe et al. (2010), Karpoff and Lou (2010), Kecskés et al. (2012), Liu and Swanson (2012) and Khan and Hai (2013) find short sellers anticipate events such as earnings surprises, financial misconduct, analyst downgrades, credit rating downgrades, mergers, repurchases, and seasoned equity offerings. Christophe et al. (2010), Henry and Koski (2010) and Khan and Hai (2013) suggest short sellers are "tipped off" or engage in price manipulation, but Drake et al. (2011), Engelberg et al. (2012) and Blau and Pinegar (2013) find short sellers are skilled at information processing, and Barone-Adesi et al. (1994) demonstrate short selling is contrarian and important to the price discovery process. Additionally, Fung and Draper (1999) and Blau (2012) provide evidence that short selling speeds the incorporation of information into futures and stock prices, respectively. We hypothesize that, if options traders act independently of or before short sellers, this would indicate informed traders engaging in the options market and supports the theory of non-redundancy. On the other hand, if options traders simply follow the lead of short sellers, then the short sellers are the more informed traders acting in the equities market, and this suggests the options market is not adding any completeness to the equities market and rejects non-redundancy.

3 Sample data and variables

In order to conduct our dynamic VAR analysis, we focus on aggregated variables throughout this paper. Specifically, although we examine all Standard and Poor's 500 (S&P 500) firms with options traded, there is only one time series for each variable which is the value-weighted average of a given variable for all firms in the sample. We obtain returns and outstanding shares for S&P 500 Index firms from the Center for Research in Security Prices (CRSP). We focus on S&P 500 firms in an effort to create a sample with relatively homogenous short sale constraints. Additionally, this sample allows us to conduct robustness tests based on index level options. Monthly short interest ratios for each firm come from the NYSE and NASDAQ exchanges. The short interest ratio for firm i in month t ($SIR_{i,t}$) is defined as:

$$SIR_{i,t} = \frac{\#\,Shares\ Short_{i,t}}{\#\,Shares\ Outstanding_{i,t}}.$$

The short interest ratios for each firm in the S&P 500 are then aggregated by market capitalization into a single short interest ratio, SIR_t. Thus, we have one observation for each month in our sample.

Optionmetrics Ivy DB provides the daily open interest, volume, and bid/ask prices across put and call contracts for each firm. We first focus on open interest in an effort to use an analogous measure to short interest. The information content of open interest is in question, however, since the literature has, to the best of our knowledge, not established a robust predictive ability of option open interest with respect to future returns.[5] The call

[5] Safieddine and Wilhelm (1996) show open interest can predict seasoned equity offerings, and Jayaraman et al. (2001) find it has predictive ability over mergers, but neither study establishes that open interest contains general predictability of stock returns.

($OIRC_t$) and put ($OIRP_t$) open interest ratios across all call and put options (e.g. all maturities and strikes) for each firm are constructed as follows:

$$OIRC(P)_{i,t} = \frac{1}{D}\sum_{d=1}^{D}\frac{Total\ open\ call\ (put)\ interest_{i,d} \times 100}{\#\, Shares\ outstanding_{i,d}},$$

where D equals the number of trading days in month t. Each firm's open interest ratio is then aggregated each month by market capitalization to form the ratio. We use open interest because it reflects all open option contracts on the underlying, which is conceptually similar to the number of outstanding shares contemporaneously sold short in the SIR measure.

Although an analogous measure to SIR, since open interest is not established as a strong predictor of future returns, it may be a weak measure of information contained in the options market. Thus, we additionally run tests using the option to stock volume ratio (O/S), which is recently identified by Roll et al. (2010) and Johnson and So (2012) as having a strong negative relation with future returns, and thus presumably contains information not incorporated in the equities market.[6] Similar to the negative relation between short interest and future returns, the relation between O/S and future returns is indicative of informed trading. Following Roll et al. (2010), we define O/S of firm i in month t as:

$$O/S_{i,t} = \frac{Total\ Dollar\ Option\ Volume_{i,t}}{Total\ Dollar\ Share\ Volume_{i,t}},$$

where the total monthly dollar options volume for each firm is computed by multiplying the total contracts traded in each option by the end-of-day quote midpoints, aggregating across all options (e.g. all maturities and strikes) listed on the firm over the month, and multiplying that value by 100 to account for the convention that each contract represents 100 equity shares. The total dollar share volume is calculated by multiplying the closing price of the stock each day by the number of daily shares traded and aggregating over the month. The option-to-stock volume ratios for each firm in the S&P 500 are then aggregated each month by market capitalization into a single option-to-stock volume ratio, O/S_t.

Our aggregate short interest, option open interest, and O/S measures contain only firms that have options traded on them. Thus, the aggregate value does not include all S&P 500 firms. As an unreported robustness check, we have conducted all analyses using data for S&P 500 index options and including all S&P 500 stocks in our short interest aggregation. The results, while generally similar to those reported, are not included as they do not provide for a true test of complements versus substitutes. Specifically, stocks with no option activity clearly have no relation between short interest and option activity and the inclusion of such firms would cloud our analysis. Based on the availability of option and short interest data, our sample covers the period 1996–2011 and consists of 192 monthly aggregate observations.[7]

[6] As a robustness check, we also examine call-put volatility spreads of SPX (S&P 500) index options weighted by open interest. These unreported results are qualitatively similar to those using open interest (except where noted otherwise in the text). SPX options are used because the requirement of having call/put pairs at the same strike prices severely reduces the number of individual firms available to use in the sample. The O/S measure does not have such a requirement, thus all S&P 500 firms with options traded on their stock are in the sample.

[7] The number of observations in our study using a dynamic VAR model is comparable to that of Chang et al. (2013).

In addition to the analysis described above using monthly data, we closely replicate our approach using daily data for robustness. The Securities and Exchange Commission adopted Regulation SHO (Reg SHO) as a pilot program which required exchanges to provide short sale volume data starting in January, 2005. Reliable daily data was collected through the end of December, 2006, after which the pilot program was phased out. This data differs from short interest in that, while short interest provides a snapshot in time of how many shares are short relative to the total number of shares outstanding, short volume represents the number of shares sold sort on a particular day without accounting for any short positions that were covered on that day. Nevertheless, studies such as Diether et al. (2009a, b), Engelberg et al. (2012) and Boehmer and Wu (2013) show that there is information in these Reg SHO trades. Thus, we utilize this data for our daily analyses by scaling the short volume by the total daily volume of shares traded as reported by the exchanges.[8]

4 Empirical methods

To address the issues discussed above, we develop an empirical framework that helps us test whether short selling and options trading are complements or substitutes and whether short sellers and options traders are informed traders. We choose time-series methods for several reasons. First, it allows us to explore the dynamic relation between short selling and option trading. Second, unlike event studies, it avoids the endogeneity inherent in new option listings. Lastly, it allows us to simultaneously investigate the substitutability of short selling and options trading and the relative informativeness of the trades.

4.1 Short sales and options trading: Substitutes or complements?

To see whether short interest (SIR) and option trades (OIR: open interest of calls or puts) are complements or substitutes, we look at the dynamic relation between the two variables using the following regressions:

$$SIR_t = \alpha + \sum_{j=1}^{m} \alpha_j SIR_{t-j} + \sum_{j=0}^{m} \beta_j OIR_{t-j}, \tag{1}$$

$$OIR_t = \alpha + \sum_{j=1}^{m} \alpha_j OIR_{t-j} + \sum_{j=0}^{m} \beta_j SIR_{t-j}. \tag{2}$$

In Eqs. (1) and (2), we include the contemporaneous OIR and SIR, respectively. If the null hypothesis, H_0: $\sum_{j=0}^{m} \beta_j = 0$, is rejected and $\sum_{j=0}^{m} \beta_j$ is negative (positive) in (1), then open interest of calls (or puts) is substituting (complementing) short interest. That is, in this analysis we focus on the (cumulative) net effect of a variable on the dependent variable provided by the sum of the coefficients for current and lagged variables to tell whether two variables are substitutes or complements. Similarly, if the null hypothesis, H_0: $\sum_{j=0}^{m} \beta_j = 0$, is rejected and $\sum_{j=0}^{m} \beta_j$ is negative (positive) in (2), then short interest is substituting (complementing) open interest of calls (or puts).

[8] This analysis is not the focus of our study because of the limited time period in which Reg SHO was active.

4.2 Informed short sellers and two-sided regression-based causality tests (Sims test)

In this section, we provide a simple, parsimonious time-series model in which there is information asymmetry between potentially informed short sellers (or options traders) and other uninformed investors. In such a case, short-sale (or options trading) decisions may contain (or convey) new information about future stock returns. In fact, some short-sale (or options trading) decisions may be information events (i.e., forward-looking), while others may be non-information events (i.e., backward-looking) with respect to stock returns. The short-sale (or options trading) decision will be related to future stock returns when it is an informative event under information asymmetry. The idea is that, although informed short sellers (or options traders) and other uninformed investors observe the same financial variables such as current and past stock returns and fundamentals, other uninformed investors may not recover all the information that short sellers (or options traders) use in short sales (or options trading).[9] Our model is very useful because it provides a regression model that tests the predictive power of short sales (or options trading) under potential information asymmetry. A practical question is how we distinguish between the two types of short sales (or short interests): informative and non-informative. When an investor engages in a short sale, if it contains new information about future prospects of the firm (i.e., stock returns) that is not contained in the current and past values of returns and short sales, it is an informative (i.e., forward-looking) short sale and it is related to future returns. Otherwise, it is a non-informative (i.e., backward-looking) short sale. We can empirically test whether short-sale decisions are informative or not by using the following proposition of Granger causality which arises from Granger (1969) and Sims (1972, Theorem 2).

Proposition 1 *Consider the following two-sided regression*:

$$SIR_t = \alpha + \sum_{j=-m}^{m} \delta_j R_{t-j} + \varepsilon_t, \tag{3}$$

where $E(\varepsilon_t \cdot R_{t-j}) = 0$ *for all* j (=$-m, \ldots, -1, 0, 1, \ldots, m$), R_t *is the stock return at time* t, *and* SIR_t *is the short interest ratio at time* t (*this may be replaced by an options activity measure in order to examine the relation between returns and option activity*). *If the null hypothesis that all the coefficients of future returns are zero* (*i.e.*, $\delta_j = 0$ *for all* $j < 0$) *is rejected, then* SIR_t *Granger-causes* R_t.[10]

That is, we can use the two-sided regression as a means of testing the predictability of short sales (and/or options activity) for market returns, and the finding of the predictive power of short sales (and/or options activity) can be interpreted based on information asymmetry. The intuition behind this test is that including lagged values of market returns helps us control for potential feedback in short-sale decisions.

[9] We capture this intuition in a time-series concept of the non-invertibility of the moving average representation [see Box and Jenkins (1976, p. 69) and Granger and Newbold (1986, p. 145)].

[10] The complete derivation the methodology can be found in “Appendix 2”.

5 Empirical results

5.1 Nonstationary variables

In Table 1 we examine the stationarity of the various option and short interest variables used in our analysis. If a variable is non-stationary, the first-difference of the variable is needed. However, using the first-difference in a variable that is already stationary is not desirable (i.e., a potential over-differencing issue which could lead to less stable coefficient estimates). Thus, it is important to carefully identify the stationarity of each variable. The results of our Augmented Dickey–Fuller (1979) and Phillips and Perron (1988) unit root tests can be found in Table 1. We find that SIR_t, $OIRP_t$, and $OIRC_t$ are all nonstationary series, while RETURN and O/S series are stationary. This implies that we need to use the first-differenced series of these nonstationary variables in our analysis. When we consider a linear combination of these nonstationary series, these residuals (i.e., linear combinations) are stationary. This implies that a linear combination of SIR_t and $OIRP_t$ (i.e., $\mathrm{RESP_t}$), that of SIR_t and $OIRC_t$ (i.e., $\mathrm{RESC_t}$), and that of SIR_t, $OIRP_t$ and $OIRC_t$ ($\mathrm{RES3_t}$) are cointegrated. That is, we find $\mathrm{RESP_t}$, $\mathrm{RESC_t}$, and $\mathrm{RES3_t}$ are stationary. Given the observed cointegration, a VECM (vector error correction model) with an error correction term, which is a linear combination of cointegrated variables, is used when these variables are included.

Table 1 Unit root tests: sample period, 1996:03–2011:12 (Observations 188)

(i) Augmented Dickey–Fuller regression
$\Delta x_t = \alpha_0 + \alpha x_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta x_{t-i} + v_t$
(ii) Phillips–Perron regression
$x_t = b_0 + b x_{t-1} + v_t$

Variables (x_t)	Dickey–Fuller test				Phillips–Perron test			
	τ_α				$Z(t_b)$			
	1 lag	2 lags	3 lags	4 lags	1 lag	2 lags	3 lags	4 lags
$\mathrm{RETURN_t}$	−9.716	−7.046	−5.963	−5.337	−12.523	−12.499	−12.513	−12.536
$\mathrm{SIR_t}$	−1.973	−1.957	−1.946	−1.514	−2.115	−2.119	−2.119	−2.081
$\mathrm{OIRP_t}$	−1.975	−0.864	−0.690	−0.430	−0.975	−0.966	−0.900	−0.800
$\mathrm{OIRC_t}$	−1.286	−0.896	−0.703	−0.422	−1.054	−1.034	−0.955	−0.845
$\mathrm{O/S_t}$	−4.367	−3.675	−3.243	−2.752	−4.393	−4.239	−4.068	−3.904
$\mathrm{RESP_t}$	−4.308	−4.065	−3.600	−2.919	−3.961	−4.032	−3.972	−3.831
$\mathrm{RESC_t}$	−4.151	−3.945	−3.401	−2.603	−3.771	−3.857	−3.794	−3.622
$\mathrm{RES3_t}$	−4.383	−4.099	−3.787	−3.268	−4.107	−4.154	−4.110	−4.016
$\mathrm{RESPC_t}$	−3.366	−2.920	−3.442	−3.437	−3.247	−3.202	−3.275	−3.343

Critical values of *t*-statistics for both τ_α and $Z(t_b)$ are: 1 % = −3.470, 5 % = −2.879, 10 % = −2.576 (Fuller 1976, Tables 8.5.1 and 8.5.2, pp. 371–373). The details of the adjusted *t*-statistics $Z(t_b)$ can be found in the work of Phillips and Perron (1988)

$RETURN_t$ value weighted return of S&P 500 firms WITH option and short data (in other words, not all 500 firms make it into this return calculation), SIR_t short interest as a %, $OIRP_t$ total open interest of puts, $OIRC_t$ total open interest of calls, O/S_t total dollar option volume/total dollar share volume, $RESP_t$ residual in the regression of $\mathrm{SIR_t}$ on $\mathrm{OIRP_t}$, $RESC_t$ residual in the regression of $\mathrm{SIR_t}$ on $\mathrm{OIRC_t}$, $RES3_t$ residual in the regression of $\mathrm{SIR_t}$ on $\mathrm{OIRP_t}$ and $\mathrm{OIRC_t}$, $RESPC_t$ residual in the regression of $\mathrm{OIRP_t}$ on $\mathrm{OIRC_t}$

5.2 Short sales and options trading: Substitutes or complements?

The issue of whether short selling and option activity are complements or substitutes has been addressed by the literature without reaching a consensus. Table 2 displays the results testing whether options and shorts are complements or substitutes. In this analysis we focus on the (cumulative) net effect of a variable on the dependent variable provided by the sum of the coefficients for current and lagged variables as discussed in Sect. 4.1 with Eqs. (1) and (2). In general, there is strong evidence of options and short activity serving as complements for one another. When we focus on relations significant at a minimum of the 10 % level we find:

1. ΔOIRP and ΔOPIRC are neither a substitute nor a complement to ΔSIR.
2. Δ*SIR* complements Δ*OIRP* and Δ*OIRC*.
3. Δ*OIRC* complements Δ*OIRP* and Δ*OIRP* complements Δ*OIRC*.
4. Levels of *OIRP* and *OIRC* complement levels of *SIR*, and levels of *SIR* complement levels of *OIRP* and *OIRC*.
5. Levels of *OIRC* complement levels of *OIRP*, and levels of *OIRP* complement levels of *OIRC*.
6. *O/S* is neither a substitute nor a complement to Δ*SIR*, and Δ*SIR* is neither a substitute nor a complement to *O/S*.

Thus, our results are consistent with option and short interest serving as complements for one another. Our results are inconsistent with the suggestion that options and shorts serve as substitutes due to option introduction relieving short sale constraints.

5.3 Tests of informedness based on Sims (1972) bivariate, two-sided regression

The literature is mixed with respect to the information contained in options trading. While short sellers are generally considered to be informed, a comparison of the relative information contained by short sellers versus options traders has, to our knowledge, not been addressed. In Table 3 we directly test which of the various groups (short sellers and options traders) are relatively more informed. We do so using Sims (1972) two-sided regression based causality tests (see "Appendix 2" for proof).

In Table 3, Panels A through D, we use bivariate models with first-differenced *SIR*, *OIRP*, *OIRC*, and levels of *O/S* as short interest and option variables and *RETURN* for the return variable. In all panels we test both the joint and cumulative (net) effect of the variables of interest. If the null hypothesis that the coefficients of past returns are zero as a group is rejected, it implies that past returns Granger-cause the other variable (i.e., SIR or OIR or O/S). If the null hypothesis that the coefficients of future returns are zero as a group is rejected, it implies that the other variable (i.e., SIR or OIR or O/S) Granger-causes returns, and we can interpret this as evidence of an informed decision by short sales (or option trades) as we have discussed above in Sect. 4.2. The *t* test for the sum of the lagged (or future) coefficients tests if the direction (i.e., positive or negative) of the causal relation is significant.

The results in Panel A of Table 3 indicate that *RETURN* Granger-causes *SIR* and the effect is negative and significant (at the 1 % level). Thus, consistent with momentum-trading, higher returns result in lower short interest. However, *SIR* is found not to Granger-cause returns, and the direction of the effect is insignificantly positive. The combined results suggest that while short sellers increase short activity in response to lower returns,

Table 2 Complements versus substitutes

H_0 (null hypothesis)	Sum of coeff.	t-statistic	Significance level	
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRP_{t-j} + b * RESP_{t-1}$				(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−0.0489	t = −0.3487	0.7272	
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRC_{t-j} + b * RESC_{t-1}$				(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−0.0232	t = −0.2000	0.8415	
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRP_{t-j} + \sum_{j=0}^{3} \beta_j \Delta SIR_{t-j} + b * RESP_{t-1}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.4560	t = 1.9742	0.0484	
$\Delta OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRC_{t-j} + \sum_{j=0}^{3} \beta_j \Delta SIR_{t-j} + b * RESC_{t-1}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.4718	t = 1.9207	0.0548	
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRP_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRC_{t-j} + b * RESPC_{t-1}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.6178	t = 5.3574	0.0000	
$\Delta OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRC_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRP_{t-j} + b * RESPC_{t-1}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.7842	t = 4.6002	0.0000	
$SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j SIR_{t-j} + \sum_{j=0}^{3} \beta_j OIRP_{t-j}$				(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0499	t = 2.6116	0.0090	
$SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j SIR_{t-j} + \sum_{j=0}^{3} \beta_j OIRC_{t-j}$				(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0466	t = 2.7464	0.0060	
$OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRP_{t-j} + \sum_{j=0}^{3} \beta_j SIR_{t-j}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.1183	t = 2.4405	0.0147	
$OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRC_{t-j} + \sum_{j=0}^{3} \beta_j SIR_{t-j}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.1134	t = 2.2228	0.0262	
$OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRP_{t-j} + \sum_{j=0}^{3} \beta_j OIRC_{t-j}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0838	t = 2.3299	0.0198	
$OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRC_{t-j} + \sum_{j=0}^{3} \beta_j OIRP_{t-j}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.1049	t = 2.6045	0.0092	
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j O/S_{t-j}$				(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−0.0026	t = −0.1593	0.8734	
$O/S_t = \alpha + \sum_{j=1}^{3} \alpha_j O/S_{t-j} + \sum_{j=0}^{3} \beta_j \Delta SIR_{t-j}$				(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−1.0232	t = −1.3840	0.1664	

This table displays the results testing whether options and shorts are complements or substitutes. In this analysis we focus on the net effect of a variable on the dependent variable provided by the sum of the coefficients (sum of coeff.) for current and lagged variables as discussed in Sect. 4.1 with Eqs. (1) and (2)

SIR_t short interest as a %, $OIRP_t$ total open interest of puts, $OIRC_t$ total open interest of calls, O/S_t total dollar option volume/total dollar share volume

they are not well informed investors in that their increased short activity does not have a significant predictive power for future returns. Instead, short sellers seem to be backward-looking momentum traders responding to past returns.

Table 3 Tests of the information content using Sims (1972) causality tests: 1996:04–2011:12 (Observations 188)

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
Sims (1972) causality test for sample period, 1996:03–2011:12 (Observations 188)			
Panel A: ΔSIR_t on *RETURN*			
$\Delta SIR_t = \alpha + \sum_{j=-3}^{3} \gamma_j Return_{t-j}$,			(13)
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 13.5118	0.0036
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.0074	t = −3.5381	0.0004
H_0: $\gamma_j = 0$ for j = −1, −2, −3		χ^2 (3) = 5.2208	0.1563
H_0: $\sum_{j=1}^{-3} \gamma_j = 0$	0.0032	t = 1.4064	0.1596
Panel B: $\Delta OIRP$ on *RETURN*			
$\Delta OIRP_t = \alpha + \sum_{j=-3}^{3} \gamma_j Return_{t-j}$,			(13)
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 10.3692	0.0157
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	0.0044	t = 1.3900	0.1645
H_0: $\gamma_j = 0$ for j = −1, −2, −3		χ^2 (3) = 6.8312	0.0775
H_0: $\sum_{j=1}^{-3} \gamma_j = 0$	−0.0025	t = −1.2616	0.2071
Sims (1972) causality test for sample period, 1996:04–2011:12 (Observations 188)			
Panel C: $\Delta OIRC$ on *RETURN*			
$\Delta OIRC_t = \alpha + \sum_{j=-3}^{3} \gamma_j Return_{t-j}$			(13)
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 10.6984	0.0135
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	0.0056	t = 1.4750	0.1402
H_0: $\gamma_j = 0$ for j = −1, −2, −3		χ^2 (3) = 11.9407	0.0076
H_0: $\sum_{j=1}^{-3} \gamma_j = 0$	−0.0067	t = −2.3578	0.0184
Panel D: O/S on *RETURN*			
$O/S_t = \alpha + \sum_{j=-3}^{3} \gamma_j Return_{t-j}$,			(13)
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 6.1458	0.1047
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.0258	t = −2.4627	0.0138
H_0: $\gamma_j = 0$ for j = −1, −2, −3		χ^2 (3) = 22.9620	0.0000
H_0: $\sum_{j=1}^{-3} \gamma_j = 0$	−0.0567	t = −4.6843	0.0000

In this table we directly test which of the various groups (short sellers and options traders) are relatively more informed. We do so using Sims (1972) two-sided regression based causality tests in Eq. (13)

RETURN$_t$ value weighted return of S&P 500 firms WITH option and short data (in other words, not all 500 firms make it into this return calculation), *SIR*$_t$ short interest as a %, *OIRP*$_t$ total open interest of puts, *OIRC*$_t$ total open interest of calls, *O/S*$_t$ total dollar option volume/total dollar share volume

In Panel B of Table 3 we fail to find a clear directional relation between put activity and stock returns. Panel C of Table 3 shows that *RETURN* Granger-causes *OIRC* with a marginal positive effect (significance level = 0.1402), and *OIRC* Granger-causes returns with a significant negative effect. This implies that call activity increases marginally in response to higher returns, but buyers of call options are not well informed investors in that their increased call activities are not in anticipation of significantly higher future returns. Rather, they seem to be backward-looking investors marginally responding to past recent higher returns. However, considering that Lakonishok et al. (2007) show non-market maker option trades consist mostly of writing calls, these results can also be interpreted as contrarian trades by option investors, which our findings demonstrate would typically result in the capturing of option premiums since negative returns follow the (short call) option trades.

In Panel D of Table 3, *RETURN* Granger-causes *O/S* with a statistically significant negative net effect, and *O/S* Granger-causes *RETURN* with a statistically significant negative net effect. Thus, there is a feedback relation between *O/S* and *RETURN*. The results indicate that *O/S* helps better predict future returns and that, although options traders appear to be momentum traders, they are, on average and in aggregate, informed investors.

5.4 Tests of informedness based on multivariate causality tests

The bivariate analysis in Table 3 is conducted using the two-sided regression causality tests developed by Sims (1972), which we relate to potential information asymmetry. However, it does not provide lags of the dependent variable or include more than one variable of interest at a time. To further test causal relations based on multiple variables, in Table 4, we add both to our causality tests, which become usual multivariable causality tests.

In the expanded model in Panel A of Table 4, where *RETURN* is the dependent variable, we find *SIR* does not Granger-cause returns, while *OIRP* and *OIRC* Granger-cause returns. In addition, *OIRP* (*OIRC*) anticipates positive (negative) stock returns, which suggests both activities are not well informed about future stock returns or that non-market makers are net writers of calls and are informed. Panel B of Table 4, where ΔSIR is the dependent variable, displays results that indicate *RETURN* Granger-causes *SIR* marginally with a significant negative effect. This implies that short sales are responding to lower stock returns, which is consistent with Panel A of Table 3. *OIRP* and *OIRC* do not Granger-cause *SIR*, which implies that neither put nor call activities lead to short sale activities. Overall, while neither *OIRP* nor *OIRC* has the power to predict *SIR*, *SIR* activities increase in response to lower stock returns (i.e., backward-looking activities).

In Panel C of Table 4, where $\Delta OIRP$ is the dependent variable, we find that *RETURN* Granger-causes *OIRP* with a positive cumulative effect (significant at the 5 % level), which is consistent with Panel B of Table 3, implying that put activities are responding to higher stock returns. *SIR* Granger-causes *OIRP* with a positive effect, which implies that short sale activities lead put activities or put activities tend to follow higher short sales. However, *OIRC* does not Granger-cause *OIRP*, and its net effect is not significant. In Panel D of Table 4, where $\Delta OIRC$ is the dependent variable, we see that *RETURN* Granger-causes *OIRC* with a significant positive net effect, which is compatible with Panel C of Table 3. This implies that call activities respond to higher stock returns. *SIR* Granger-causes *OIRC* with a marginally positive net effect, which implies that short sale activities lead call activities or call activities tend to weakly follow higher short sales. However, put activities do not have any predictive power for call activities. Overall, indicative of a complementary relation, call activities tend to respond to higher stock returns and weakly follow higher short sale activities.

In Panel E of Table 4, *SIR* does not Granger-cause *RETURN* and the net effect is not significant. However, *O/S* Granger-causes *RETURN* with a significant net negative effect as in the two-sided regressions in Panel D of Table 3. In Panel F, *RETURN* Granger-causes *SIR* with a significant negative net effect, which is consistent with the two-sided regressions in Panel A of Table 3. *O/S* does not Granger-cause *SIR*. In Panel G, neither *RETURN* nor *SIR* Granger-causes *O/S*. Overall, these three panels indicate that *O/S* contains information about future returns, while *SIR* does not. Thus, options traders (in terms of *O/S*) appear to be informed about future stock returns.

Table 4 Tests of the information content using causality tests: 1996:04–2011:12 (Observations 188)

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
Panel A: *RETURN* regression			
$Return_t = \gamma + \sum_{j=1}^{3} a_j Return_{t-j} + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRC_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 1.3386	0.7200
H_0: $\sum_{j=1}^{3} b_j = 0$	5.7632	t = 0.8063	0.4201
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 19.5243	0.0002
H_0: $\sum_{j=-1}^{-3} c_j = 0$	60.2403	t = 4.3201	0.0000
H_0: $d_j = 0$ for j = 1, 2, 3		χ^2 (3) = 24.1435	0.0000
H_0: $\sum_{j=-1}^{-3} d_j = 0$	−58.5537	t = −4.8053	0.0000
Panel B: SIR regression			
$\Delta SIR_t = \gamma + \sum_{j=1}^{3} a_j \Delta SIR_{t-j} + \sum_{j=1}^{3} b_j Return_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRC_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 5.0751	0.1664
H_0: $\sum_{j=1}^{3} b_j = 0$	−0.0044	t = −1.8250	0.0680
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 1.3752	0.7114
H_0: $\sum_{j=-1}^{-3} c_j = 0$	−0.1154	t = −0.3983	0.6904
H_0: $d_j = 0$ for j = 1, 2, 3		χ^2 (3) = 2.0084	0.5707
H_0: $\sum_{j=-1}^{-3} d_j = 0$	0.0177	t = 0.0665	0.9470
Panel C: OIRP regression			
$\Delta OIRP_t = \gamma + \sum_{j=1}^{3} a_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} b_j Return_{t-j} + \sum_{j=1}^{3} c_j \Delta SIR_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRC_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 11.0497	0.0115
H_0: $\sum_{j=1}^{3} b_j = 0$	0.0053	t = 2.0398	0.0414
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 13.0752	0.0045
H_0: $\sum_{j=-1}^{-3} c_j = 0$	0.4369	t = 2.3054	0.0211
H_0: $d_j = 0$ for j = 1, 2, 3		χ^2 (3) = 3.1931	0.3628
H_0: $\sum_{j=-1}^{-3} d_j = 0$	0.1295	t = 0.3727	0.7094
Panel D: OIRC regression			
$\Delta OIRC_t = \gamma + \sum_{j=1}^{3} a_j \Delta OIRC_{t-j} + \sum_{j=1}^{3} b_j Return_{t-j} + \sum_{j=1}^{3} c_j \Delta SIR_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRP_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 9.2715	0.0259
H_0: $\sum_{j=1}^{3} b_j = 0$	0.0060	t = 1.8195	0.0688
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 8.9870	0.0295
H_0: $\sum_{j=-1}^{-3} c_j = 0$	0.3570	t = 1.5623	0.1182
H_0: $d_j = 0$ for j = 1, 2, 3		χ^2 (3) = 2.8925	0.4085
H_0: $\sum_{j=-1}^{-3} d_j = 0$	−0.4125	t = −0.7540	0.4508
Panel E: *RETURN* regression			
$Return_t = \gamma + \sum_{j=1}^{3} a_j Return_{t-j} + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} c_j \ O/S_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 1.8156	0.6115
H_0: $\sum_{j=1}^{3} b_j = 0$	7.8366	t = 1.0781	0.2819
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 10.9209	0.0122
H_0: $\sum_{j=-1}^{-3} c_j = 0$	−2.1471	t = −2.8372	0.0046

Table 4 continued

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
Panel F: SIR regression			
$\Delta SIR_t = \gamma + \sum_{j=1}^{3} a_j \Delta SIR_{t-j} + \sum_{j=1}^{3} b_j Return_{t-j} + \sum_{j=1}^{3} c_j \, O/S_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 9.5630	0.0227
H_0: $\sum_{j=1}^{3} b_j = 0$	−0.0063	t = −2.8114	0.0049
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 1.0838	0.7810
H_0: $\sum_{j=-1}^{-3} c_j = 0$	−0.0123	t = −0.7957	0.4262
Panel G: O/S regression			
$O/S_t = \gamma + \sum_{j=1}^{3} a_j O/S_{t-j} + \sum_{j=1}^{3} b_j Return_{t-j} + \sum_{j=1}^{3} c_j \Delta SIR_{t-j},$			
H_0: $b_j = 0$ for j = 1, 2, 3		χ^2 (3) = 3.0279	0.3873
H_0: $\sum_{j=1}^{3} b_j = 0$	−0.0095	t = −1.0039	0.3154
H_0: $c_j = 0$ for j = 1, 2, 3		χ^2 (3) = 5.3049	0.1508
H_0: $\sum_{j=-1}^{-3} c_j = 0$	−1.0300	t = −1.7228	0.0849

In this table we directly test which of the various groups (short sellers and options traders) are relatively more informed in a multivariable framework. We do so using Sims (1972) two-sided regression based causality tests in Eq. (13)

RETURN$_t$ value weighted return of S&P 500 firms WITH option and short data (in other words, not all 500 firms make it into this return calculation), *SIR$_t$* short interest as a %, *OIRP$_t$* total open interest of puts, *OIRC$_t$* total open interest of calls, *O/S$_t$* total dollar option volume/total dollar share volume

5.5 Tests of informedness based on bivariate models

While the literature has provided evidence that suggests that both short interest and option activity may be informed, the question of which group is relatively more informed remains unanswered. Our results in Tables 3 and 4 are consistent with options traders being relatively more informed. In Table 5 we focus on the relation between short interest and option activity to test more directly who are more informed traders are between short traders and options traders.

In Panels A and B of Table 5, we use two-sided regressions, taking into account potential cointegration between variables. In Panel A, which uses the first differences of the variables in our VECM, *OIRP* and *SIR* do not Granger cause each other, and the net effect is not significant either. This suggests that when we take into account the cointegration between the two variables, the net effect is not clear. In Panel B of Table 5, we examine the relation between *SIR* and *OIRC*. The results indicate that *OIRC* and *SIR* do not Granger cause each other, and the net effect is not significant. This again suggests that when we take into the cointegration between the two variables, the net effect is not clear. Overall, short sales are not significantly affected by either put or call trades.

In Panels C through F of Table 5, we examine dynamic relations between short interest and option activity using conventional (i.e., one-sided) VAR based causality tests. Overall, for Panels C and D, *OIRP* marginally helps better predict *SIR* with a net significant negative effect on *SIR*. However, the direction of the net effect of *OIRP* on *SIR* is against the conventional prediction.

In Panel E, we find that *OIRC* helps better predict *SIR* with a negative net effect (significant at the 10 % level). In Panel F, we find that *SIR* helps predict *OIRC* with an

Table 5 Tests of the information content using Sims (1972) causality tests: 1996:04–2011:12 (Observations 188)

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
Sims (1972) causality test for sample period, 1996:03–2011:12 (Observations 188)			
Panel A: ΔSIR_t on $\Delta OIRP$			
$\Delta SIR_t = \alpha + \sum_{j=-3}^{3} \gamma_j \Delta OIRP_{t-j} + b * RESP_t,$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3, and b = 0		χ^2 (3) = 1.8571	0.6026
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.0275	t = −0.2664	0.7899
H_0: $\gamma_j = 0$ for j = −1, −2, −3, and b = 0		χ^2 (3) = 5.3263	0.1494
H_0: $\sum_{j=-1}^{-3} \gamma_j = 0$	0.1373	t = 1.0675	0.2858
Panel B: SIR on OIRC			
$\Delta SIR_t = \alpha + \sum_{j=-3}^{3} \gamma_j \Delta OIRC_{t-j} + b * RESC_t,$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3, and b = 0		χ^2 (3) = 2.9885	0.3934
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.0239	t = −0.2654	0.7907
H_0: $\gamma_j = 0$ for j = −1, −2, −3, and b = 0		χ^2 (3) = 4.7875	0.1880
H_0: $\sum_{j=-1}^{-3} \gamma_j = 0$	0.0844	t = 0.8253	0.4092
Panel C: SIR on OIRP			
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} \gamma_j \Delta OIRP_{t-j} + d * RESP_{t-1},$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 6.2191	0.1014
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.1961	t = −1.9035	0.0570
Panel D: OIRP on SIR			
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3} b_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} \gamma_j \Delta SIR_{t-j} + d * RESP_{t-1},$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 10.8200	0.0127
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	0.3028	t = 1.4193	0.1558
Panel E: SIR on OIRC			
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} \gamma_j \Delta OIRC_{t-j} + d * RESC_{t-1},$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 7.6590	0.0536
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.1674	t = −1.7069	0.0878
Panel F: OIRC on SIR			
$\Delta OIRC_t = \alpha + \sum_{j=1}^{3} b_j \Delta OIRC_{t-j} + \sum_{j=1}^{3} \gamma_j \Delta SIR_{t-j} + d * RESC_{t-1},$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 9.1423	0.0275
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	0.2628	t = 1.1134	0.2655
Panel G: ΔSIR on O/S			
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} \gamma_j O/S_{t-j},$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 0.4445	0.9309
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.0006	t = −0.0371	0.9704
Panel H: O/S on ΔSIR			
$O/S_t = \alpha + \sum_{j=1}^{3} b_j O/S_{t-j} + \sum_{j=1}^{3} \gamma_j \Delta SIR_{t-j},$			
H_0: $\gamma_j = 0$ for j = 1, 2, 3		χ^2 (3) = 4.4626	0.2156

Table 5 continued

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
H_0: $\sum_{j=1}^{3} \gamma_j = 0$	−0.8681	t = −1.4228	0.1548

In this table we directly test which of the various groups (short sellers and options traders) are more informed using two-sided regressions, taking into account potential cointegration between variables

$RETURN_t$ value weighted return of S&P 500 firms WITH option and short data (in other words, not all 500 firms make it into this return calculation), SIR_t short interest as a %, $OIRP_t$ total open interest of puts, $OIRC_t$ total open interest of calls, O/S_t total dollar option volume/total dollar share volume

insignificant net effect. Overall, for Panels E and F, *OIRC* helps better predict SIR with a net negative effect on *SIR*.

In Panels G and H, we do not find a causal relation between *O/S* and *SIR* or between *SIR* and *O/S*. Thus, the evidence suggests that options traders and short traders act independently of one another.

The results of Table 5 indicate that option interest helps predict short activity, and that short activity helps predict option interest. We find that short activity decreases following an increase in option volume. However, when we consider both volume and price of options via the O/S measure, there is no longer a significant relation.

5.6 Tests of informedness based on trivariate models

We extend the tests of Table 5 by including put, call, and short activity in our model at the same time. Note that we do not examine *O/S* in this table as it does not have a natural pair as is the case for puts and calls. The results are reported in Table 6. In Panel A of Table 6, neither *OIRP* nor *OIRC* helps predict *SIR*. Thus, when we include all three variables of interest, option activity does not have predictive power for short activity.

In Panel B of Table 6, we find that *SIR* helps predict *OIRP*, but its net effect is insignificant. In Panel C of Table 6, *SIR* helps predict *OIRC,* but its net effect is insignificant. When both types of option activity are included in the model with short activity, we find consistent results. Specifically, short interest helps predict option activity and option activity does not predict short interest. However, the lack of significance in the net effect yields no clear conclusions about which group is relatively more informed in this analysis.

5.7 Robustness

We have conducted a battery of robustness tests. Our robustness checks include: (1) different measures of option open interest, (2) using levels of non-stationary variables, (3) using index level option volatility spreads, (4) using equal-weighted aggregate data, and (5) using daily data for shorts and options. The alternate option open interest measures include total option open interest (call open interest plus put open interest) and net put open interest (put open interest less call open interest). Open interest results are qualitatively identical regardless of the measures used.

Using the levels of non-stationary variables is less appropriate than the first-differenced results reported. Nonetheless, we have conducted all analyses using the levels of non-stationary variables. We still find that option and short interest serve as complements for

Table 6 Tests of the information content using causality tests: 1996:05–2011:12 (Observations 188)

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
Panel A: SIR regression			
$\Delta SIR_t = \gamma + \sum_{j=1}^{3} a_j \Delta SIR_{t-j} + \sum_{j=1}^{3} b_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRC_{t-j} + d * RES3_{t-1}$,			
H_0: $b_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 2.1029	0.5513
H_0: $\sum_{j=1}^{3} b_j = 0$	−0.2201	t = −0.7464	0.4554
H_0: $c_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 2.1989	0.5322
H_0: $\sum_{j=1}^{3} c_j = 0$	0.0423	t = 0.1480	0.8823
Panel B: OIRP regression			
$\Delta OIRP_t = \gamma + \sum_{i=1}^{3} a_i \Delta OIRP_{t-i} + \sum_{i=1}^{3} b_j \Delta SIR_{t-i} \sum_{i=1}^{3} c_j \Delta OIRC_{t-i} + d * RES3_{t-1}$,			
H_0: $b_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 11.0957	0.0112
H_0: $\sum_{j=1}^{3} b_j = 0$	0.2919	t = 1.3671	0.1716
H_0: $c_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 3.4924	0.3217
H_0: $\sum_{j=1}^{3} c_j = 0$	0.1173	t = 0.3248	0.7453
Panel C: OIRC regression			
$\Delta OIRC_t = \gamma + \sum_{j=1}^{3} a_j \Delta OIRC_{t-j} + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRP_{t-j} + d * RES3_{t-1}$,			
H_0: $b_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 9.1341	0.0276
H_0: $\sum_{j=1}^{3} b_j = 0$	0.2513	t = 1.0046	0.3151
H_0: $c_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 3.4775	0.3239
H_0: $\sum_{j=1}^{3} c_j = 0$	−0.3375	t = −0.6083	0.5430

In this table we directly test which of the various groups (short sellers and options traders) are more informed using multivariable regressions, taking into account potential cointegration between variables

$RETURN_t$ value weighted return of S&P 500 firms WITH option and short data (in other words, not all 500 firms make it into this return calculation), SIR_t short interest as a %, $OIRP_t$ total open interest of puts, $OIRC_t$ total open interest of calls, O/S_t total dollar option volume/total dollar share volume

one another using the levels of non-stationary variables. However, the results using levels are qualitatively different from those using first differences. Specifically, when using levels, the results indicate that option interest follows short interest. This would suggest that options traders take their cue from short traders in deciding when to trade. Thus, correctly controlling for the non-stationarity of option open interest proves to be important.

We examine index (S&P 500) level option volatility spreads as an additional measure of option activity. Results are generally similar to what we find for option open interest, but differ from our results using the ratio of option volume to stock volume. Specifically, we find that index level volatility spreads do not help better predict returns. We note that the issue of a possible complementary or substitute relation is not appropriate for index level data as several firms in the S&P 500 lack available traded options. Thus, the possibility to substitute from short interest to options or vice versa is not possible.

We use equal-weighted aggregate data for one robustness analysis. It may be that value-weighting, as we have done throughout the paper, biases our results toward the observed complementary relation between short interest and option activity. Although we focus on firms in the S&P 500 in order to provide a relatively homogenous sample with respect to short sale constraints, there is likely some heterogeneity in the sample. Specifically, larger firms are likely less short sale constrained than smaller firms which reduces the need to substitute between shorts and options. Value-weighting places greater emphasis on these less constrained firms and may induce the observed relation. Thus, we repeat our analysis using equal-weighted data which places more emphasis on relatively more short sale constrained stocks.

The results in "Appendix 4" show similar results regarding whether options and shorts are complements or substitutes. In general, there is strong evidence of options and short activity serving as complements for one another, which suggests the relation is not sensitive to the use of value-weighted or equal-weighted S&P index data.[11] Although the aggregation technique is only likely to influence the complement versus substitute analysis, we repeat all analyses using equal-weighted data.[12]

Finally, we use daily data instead of monthly data and repeat our analysis. Daily data may be better suited to detecting informed trades given that it may more closely match the investment horizon of short and option traders. However, we only have daily short interest data for a limited period from 2005 to 2006 which yields approximately 500 daily observations. Ultimately, we report results throughout using monthly data given that the longer time period covered by such data yields results that are more likely to generalize. Our results, with one exception, are qualitatively identical using daily data. The one exception is that when using daily data we no longer find that short traders are backward-looking momentum traders. However, we still find that short traders are uninformed.[13]

6 Conclusion

We examine the dynamic relation between aggregate returns, short trading, and option activity in the US over the period 1996–2011. Our goal is threefold: (1) to determine whether short selling and options trading are substitutes or not, (2) to explore if the options market is non-redundant to the equities market, and (3) to ascertain the relative informedness between short selling and options trading. Counter to the findings of event studies around option listings, we find that short interest and option open interest are complements, not substitutes. Thus, short sellers do not leave the equities market in preference for the options market. Our results further support studies such as Lamont and Stein (2004) and Battalio and Schultz (2011).

Additionally, consistent with the findings of Lamont and Stein (2004), the results suggest that, in aggregate, short sellers are generally momentum traders, as their activity

[11] As we find in "Appendix 3", the unit root tests and cointegration tests show that the results are qualitatively the same as in the case of the value-weighted S&P index data. That is, we find that SIR_t, $OIRP_t$, and $OIRC_t$ are all nonstationary series, while *RETURN* and *O/S* series are stationary. We further find that a linear combination of SIR_t and $OIRP_t$ (i.e., $RESP_t$), that of SIR_t and $OIRC_t$ (i.e., $RESC_t$), and that of SIR_t, $OIRP_t$ and $OIRC_t$ ($RES3_t$) are cointegrated.

[12] Overall, we find some difference in the results using equal-weighted S&P index data compared with those using value-weighted S&P index data. The different results suggest that for small firms (1) the response of *OIRP* and *OIRC* to past *RETURN* is neither strong nor clear compared with that of large firms, (2) the response of *SIR* to past *RETURN* is not clear compared with that of large firms, (3) *O/S* may have less predictive power for future returns compared with large firm future returns, (4) the dynamic effect of *RETURN* on *O/S* is stronger and clear compared with that of large firms, (5) *O/S* Granger-causes *SIR*, although its effects on *SIR* remains insignificant as in the case of the value-weighted data, and (6) both *OIRP* and *OIRC* Granger-cause *SIR*. The detailed estimation results using equal-weighted index data are available upon request.

[13] Results not reported for brevity but are available upon request.

responds to past negative return performance with increased short interest. We add to the existing literature by showing aggregate option open interest, like short selling, is also backward-looking. Further results indicate that neither short interest nor option open interest contains information about future equity returns. However, when we employ the option-to-stock volume ratio (O/S) measure in our analysis we find that options traders are informed in that their activity helps predict future returns, while short interest still contains no return predictability. The O/S measure's return predictability while controlling for past returns and short interest indicates the options market contains information not present in the equities market. Thus, taking all the evidence together, options traders are relatively more informed than both traditional equity and short traders, rendering the options market non-redundant and not a substitute for short selling.

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Appendix 1: Variable definitions

Variable name	Definition
SIR	Short interest as a % of shares outstanding
RETURN	Value-weighted return of S&P 500 firms with option and short data
OIRP	Total open interest of puts
OIRC	Total open interest of calls
O/S	Total dollar option volume divided by total dollar share volume

Appendix 2: Derivation of Sims' test in the context of short interest and returns

We utilize a theorem in time-series econometrics, which states that any time-series process has both invertible and non-invertible representations (see Fuller 1976, pp. 64–66, Theorem 2.6.4). Although stock returns, R_t, may follow a general autoregressive moving-average (i.e., ARMA(p,q)) process, for expositional simplicity, we assume that other uninformed investors, observing current and past stock returns, infer a first-order (invertible) moving average, MA(1) [i.e., ARMA (0,1)], process of the returns:

$$R_t = (1 - \lambda L)u_t, \qquad |\lambda| < 1.0, \tag{4}$$

where R_t is the stock return at time t, L is the lag (or backshift) operator (i.e., $L^n R_t = R_{t-n}$), u_t is white noise with $\mathrm{var}(u_t) = \sigma_u^2$, and λ is a parameter that indicates the contribution of u_{t-1} to R_t. The autocovariance functions (ACFs) for this MA(1) return process are[14]:

[14] For expositional simplicity, we use an MA(1) model of the return process. Any higher order representation of returns yields the same dynamic relations with more complicated computations.

$$\begin{aligned} var(R_t) &= (1+\lambda^2)\sigma_u^2, \\ cov(R_t, R_{t-1}) &= -\lambda\sigma_u^2, \\ cov(R_t, R_{t-k}) &= 0, \quad \text{for } k \geq 2. \end{aligned} \tag{5}$$

On the other hand, suppose that informed short sellers (or options traders), observing the same current and past stock returns, infer the following (non-invertible) MA(1) process of the returns:

$$R_t = (1-\lambda^{-1}L)v_t, \qquad |\lambda| < 1.0, \tag{6}$$

where v_t is white noise with $var(v_t) = \sigma_v^2$. The ACFs for this MA(1) return process are:

$$\begin{aligned} var(R_t) &= (1+\lambda^{-2})\sigma_v^2, \\ cov(R_t, R_{t-1}) &= -\lambda^{-1}\sigma_v^2, \\ cov(R_t, R_{t-k}) &= 0, \quad \text{for } k \geq 2. \end{aligned} \tag{7}$$

It is noted that if we set $\sigma_v^2 = \lambda^2\sigma_u^2$, then the ACFs in (5) and (7) are identical. Since the return process can be identified in practice by the observed ACFs, the identical ACFs imply that stock return processes in (4) and (6) represent the same return process. That is, for a given return process, uninformed investors and informed short sellers (or options traders) may infer different MA(1) processes.[15]

In addition, it is noted that σ_v^2 is smaller than σ_u^2:

$$\sigma_v^2 < \sigma_u^2. \tag{8}$$

This is because $\sigma_v^2 = \lambda^2\sigma_u^2$ and $|\lambda| < 1.0$. This means that the variance of the one-step-ahead forecast error of the return process in (6) by informed short sellers (i.e., σ_v^2) would be smaller than the corresponding variance of the return process in (4) by other uninformed investors (i.e., σ_u^2). However, unlike the u_t process, the v_t process cannot be fully recovered by other uninformed investors from the information about current and past values of stock returns because the process is not invertible. That is, although both short sellers and other uninformed investors observe the same (current and past) returns, under information asymmetry, informed short sellers with a larger information set, $\Omega_t^* = \{R_{t-j}, v_{t-j}, u_{t-j}, \text{ for } j \geq 0\}$, can forecast future returns better than other uninformed investors with a smaller information set, $\Omega_t = \{R_{t-j}, u_{t-j}, \text{ for } j \geq 0\}$.

We obtain an important alternative insight by comparing the corresponding autoregressive representations (ARR) of the moving average representations (MAR) of stock return processes $\{R_t\}$ in (4) and (6):

$$u_t = (1-\lambda L)^{-1}R_t = \sum_{j=0}^{\infty}\lambda^j R_{t-j}, \quad \text{and} \tag{9}$$

$$v_t = (1-\lambda^{-1}L)^{-1}R_t = -(\lambda L^{-1})(1-\lambda L^{-1})^{-1}R_t = -\sum_{j=1}^{\infty}\lambda^j R_{t+j}. \tag{10}$$

[15] The return process in (4) with innovation u_t is an invertible MAR because the root of the determinant of the MAR of R_t is >1 (i.e., det $[1 - \lambda z] = 0$, for $z = \lambda^{-1}$). However, the return process with the innovations v_t in (6) is a non-invertible MAR because the root of the determinant is <1 (i.e., det $[1 - \lambda^{-1} z] = 0$, for $z = \lambda$).

Note that the innovations $\{u_t\}$ in the other uninformed investors' return process are backward-looking, whereas the innovations $\{v_t\}$ in the informed short sellers' return process are forward-looking.[16]

How is this information asymmetry between informed short sellers and other uninformed investors related to the dynamic relation between short sales and stock returns (i.e., the predictive power of short sales)? Suppose that short sellers have an informational advantage in that they can forecast the firm's future prospects (or overvaluation) better than other uninformed investors by observing v_t. If informed short sellers use this information in their short-sale decisions, their short sales (or short interest ratio, SIR_t) will be a function of innovation v_t that they observe but other uninformed investors do not:

$$SIR_t = f(v_t) = \sum_{i=0}^{\infty} (\theta_i L^i) v_t = \sum_{i=0}^{\infty} \theta_i v_{t-i}, \quad \text{with} \quad \sum_{i=0}^{\infty} \theta_i^2 < \infty \tag{11}$$

Then, by using v_t in (10), short interest and stock return processes will be related as follows:

$$\begin{aligned} SIR_t &= \sum_{i=0}^{\infty} (\theta_i L^i) v_t = \sum_{i=0}^{\infty} (\theta_i L^i) \left\{ \left(1 - \lambda^{-1} L\right)^{-1} R_t \right\} \\ &= \sum_{i=0}^{\infty} (\theta_i L^i) \left(- \sum_{j=1}^{\infty} \lambda^j R_{t+j} \right) = \sum_{j=-\infty}^{\infty} \delta_j R_{t-j} \end{aligned} \tag{12}$$

where δ_j for $j = -\infty, \ldots, -2, -1, 0, 1, 2, \ldots, \infty$ is a function of θ_i and λ^j. That is, the informed short sales will be a linear combination of *future*, current, and past returns; thus, they will be forward-looking.[17]

In contrast, suppose that short sellers do not have an informational advantage or they simply do not make short-sale decisions based on their informational advantage. Then, the uninformed short sales will be a function of the innovation that other uninformed investors observe, u_t:

$$SIR_t = f(u_t) = \sum_{i=0}^{\infty} (\theta_i L^i) u_t = \sum_{i=0}^{\infty} \theta_i u_{t-1}, \quad \text{with} \quad \sum_{i=0}^{\infty} \theta_i^2 < \infty \tag{13}$$

Then, by using u_t in (9), uninformed short sales and stock return processes will be related as follows:

[16] The innovations $\{u_t\}$ are represented by a square summable linear combination of current and past values of the R_t's (i.e., u_t lies in the space spanned by current and lagged R_t's). However, the innovations $\{v_t\}$ are represented by a square summable linear combination of future values of R_t's (i.e., v_t lies in the space spanned by future R_t's). This is because if we solve the relation in (10) backwards, the right-hand side is not square summable.

[17] In practice, since short sellers do not have perfect foresights, (12) will be

$$SIR_t = \sum_{j=0}^{\infty} \delta_j R_{t-j} + E_t\left[\sum_{j=-\infty}^{-1} \delta_j R_{t-j} \right]. \tag{12'}$$

$$\begin{aligned} SIR_t &= \sum_{i=0}^{\infty}(\theta_i L^i)\mathrm{u}_t = \sum_{i=0}^{\infty}(\theta_i L^i)(1-\lambda \mathrm{L})^{-1}\mathrm{R}_t \\ &= \sum_{i=0}^{\infty}(\theta_i L^i)\left(\sum_{j=0}^{\infty}\lambda^j \mathrm{R}_{t-j}\right) = \sum_{k=0}^{\infty}\delta_k \mathrm{R}_{t-k}, \end{aligned} \tag{14}$$

where δ_k for k = 0, 1, 2, …, ∞ is a function of θ_i and λ^j. That is, in this case, the uninformed short sales will only reflect the past and current returns and will not be related to future returns; thus, they will be backward-looking. To summarize, we have shown that under information asymmetry, informed (or informative) short sales (or short interests) are related not only to past and current returns but also to future returns. In contrast, in the absence of information asymmetry, uninformed (or non-informative) short sales (or short interests) are not related to future returns.

Appendix 3: Unit root tests: sample period, 1996:03–2011:12 (Observations 188)

Using equal-weighted aggregate data

(i) Augmented Dickey–Fuller regression
$\Delta x_t = a_0 + a x_{t-1} + \sum_{i=1}^{m}\gamma_i \Delta x_{t-i} + v_t$
(ii) Phillips–Perron regression
$x_t = b_0 + b x_{t-1} + v_t$.

Variables (x_t)	Dickey–Fuller test				Phillips–Perron test			
	τ_α				$Z(t_b)$			
	1 lag	2 lags	3 lags	4 lags	1 lag	2 lags	3 lags	4 lags
$RETURN_t$	−10.254	−7.469	−6.100	−5.894	−11.885	−11.807	−11.789	−11.808
SIR_t	−1.678	−1.713	−1.683	−1.484	−1.742	−1.767	−1.778	−1.769
$OIRP_t$	−1.270	−1.077	−1.026	−0.919	−1.120	−1.121	−1.098	−1.061
$OIRC_t$	−1.493	−1.139	−1.072	−0.922	−1.282	−1.269	−1.221	−1.158
O/S_t	−5.352	−4.449	−4.305	−3.699	−7.052	−7.068	−7.223	−7.295
$RESP_t$	−3.226	−3.071	−2.732	−2.393	−2.850	−2.952	−2.940	−2.870
$RESC_t$	−3.958	−3.593	−2.936	−2.495	−3.216	−3.358	−3.311	−3.175
$RES3_t$	−3.719	−3.439	−2.866	−2.450	−3.098	−3.229	−3.193	−3.076
$RESPC_t$	−3.741	−2.887	−3.181	−2.655	−3.278	−3.230	−3.201	−3.149

Critical values of *t*-statistics for both τ_α and $Z(t_b)$ are: 1 % = −3.470, 5 % = −2.879, 10 % = −2.576 (Fuller 1976, Tables 8.5.1 and 8.5.2, pp. 371–373). The details of the adjusted *t*-statistics $Z(t_b)$ can be found in the work of Phillips and Perron (1988)

$RETURN_t$ value weighted return of S&P 500 firms WITH option and short data (in other words, not all 500 firms make it into this return calculation), *SIR_t* short interest as a %, *$OIRP_t$* total open interest of puts, *$OIRC_t$* total open interest of calls, *O/S_t* total dollar option volume/total dollar share volume, *$RESP_t$* residual in the regression of SIR_t on $OIRP_t$, *$RESC_t$* residual in the regression of SIR_t on $OIRC_t$, *$RES3_t$* residual in the regression of SIR_t on $OIRP_t$ and $OIRC_t$, *$RESPC_t$* residual in the regression of $OIRP_t$ on $OIRC_t$

Appendix 4: Complements versus substitutes: equal-weighted aggregate data

H_0 (null hypothesis)	– Sum of coeff.	Chi square statistic t-statistic	Significance level
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRP_{t-j} + b * RESP_{t-1}$			(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−0.3323	t = −1.3141	0.1888
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRC_{t-j} + b * RESC_{t-1}$			(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−0.2931	t = −1.1814	0.2375
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRP_{t-j} + \sum_{j=0}^{3} \beta_j \Delta SIR_{t-j} + b * RESP_{t-1}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.2456	t = 2.0759	0.0379
$\Delta OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRC_{t-j} + \sum_{j=0}^{3} \beta_j \Delta SIR_{t-j} + b * RESC_{t-1}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.2507	t = 1.7668	0.0772
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRP_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRC_{t-j} + b * RESPC_{t-1}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.5170	t = 3.5076	0.0005
$\Delta OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta OIRC_{t-j} + \sum_{j=0}^{3} \beta_j \Delta OIRP_{t-j} + b * RESPC_{t-1}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.8978	t = 5.0203	0.0000
$SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j SIR_{t-j} + \sum_{j=0}^{3} \beta_j OIRP_{t-j}$			(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0708	t = 1.7560	0.0791
$SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j SIR_{t-j} + \sum_{j=0}^{3} \beta_j OIRC_{t-j}$			(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0890	t = 2.3807	0.0173
$OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRP_{t-j} + \sum_{j=0}^{3} \beta_j SIR_{t-j}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0198	t = 1.3483	0.1776
$OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRC_{t-j} + \sum_{j=0}^{3} \beta_j SIR_{t-j}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0318	t = 1.8032	0.0714
$OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRP_{t-j} + \sum_{j=0}^{3} \beta_j OIRC_{t-j}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0450	t = 1.2636	0.2064
$OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j OIRC_{t-j} + \sum_{j=0}^{3} \beta_j OIRP_{t-j}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0808	t = 2.0181	0.0436
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j O/S_{t-j}$			(1)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	0.0175	t = 0.3692	0.7120
$O/S_t = \alpha + \sum_{j=1}^{3} \alpha_j O/S_{t-j} + \sum_{j=0}^{3} \beta_j \Delta SIR_{t-j}$			(2)
H_0: $\sum_{j=0}^{3} \beta_j = 0$	−1.5906	t = −2.1717	0.0299

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