The dynamic relation between short sellers, option traders, and aggregate returns

R. Jared Delisle and Bong Soo Lee and Nathan Mauck

Washington State University, Florida State University, University of Missouri-Kansas City

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R. Jared DeLisle
Washington State University
j.delisle@wsu.edu
(360) 546-9169

Bong Soo Lee
Florida State University
blee2@cob.fsu.edu
(850) 644-4713

Nathan Mauck
University of Missouri - Kansas City
mauckna@umkc.edu
(816) 235-6113

Abstract:
Contrary to existing event studies around option listing introductions, we show short selling and options trading are complements, rather than substitutes. Further, while a plethora of literature demonstrates both short sellers and option traders are informed traders, relatively little is known about which group is relatively more informed. The results of our dynamic tests indicate that options traders are relatively more informed and that short sellers are backward-looking. Our results support the claim that options markets are non-redundant.

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I. Introduction

There is a great deal of literature providing evidence establishing both short sellers and option traders as "informed" investors. The information contained in option trades is often viewed as evidence of non-redundancy and suggests that the options market contains information not present in the equities market, which includes short selling. However, relatively little is known about the relation between short selling and options traders, and even less is known about the dynamic relation. In this paper, we empirically investigate the dynamic 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 using methodology based on Sims (1972).

We focus on three issues:

1) Are short selling and option trading substitutes or complements?

2) Does aggregate option trading add to market completeness (i.e., is the options market non-redundant)?

3) Who is relatively more informed between short sellers and option traders?

The first issue, whether short selling and option 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. In their model, Diamond and Verrecchia (1987) agree that options reduce short selling costs, but disagree that short sale constraints necessarily bias prices upward. Diamond and Verrecchia (1987) also propose that unexpected short selling is indicative of bad news, which is empirically confirmed by Aitken, Frino, McCorry, and Swan (1998).

There has been further empirical evidence (e.g., Sorescu (2000) and 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 substituting 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, Danielsen, and Sorescu (2006) explicitly use stock option status as an indicator of lessened short sale constraints.

Yet, not all studies are consistent in revealing shorting and options as substitutes. For example, Lakonishok, Lee, Pearson, and Poteshman (2007) document non-market maker investors are net writers of options, with the majority of their open interest in call options. Evans, Geczy, Musto, and Reed (2009) provide evidence that option 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 (2011b) find no evidence of substitutability between short sales and bearish option trades. These findings place short selling and option markets not as substitutes, but rather as complements: higher option trading activity would coincide with higher short selling, but, according to hedging argument, not necessarily vice versa.

Given that Chan, Chung, and Fong (2002) find informed traders operate in the equities market, and Danielsen, van Ness, and Warr (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, Pathak, and Ritter (2005) and Boehmer, Jones, and Zhang (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, Lim, and Verwijmeren (2012) notice volume and liquidity decreased for options on stocks that fell under the U.S. 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. Furthermore, Blau and Brough (2011a) find that short selling activity is endogenous to the decision to list the stock on an options exchange, as market makers who trade options want the ability to easily short equities in their delta hedging activities. These findings make previous event studies establishing substitutability by associating option listing decisions and subsequent stock returns questionable.

Prior literature focuses on static tests such as an event study methodology to examine option exchange listings. We focus on stocks that have options traded on them and use dynamic tests that 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. Contrary to the findings of event studies around option listings, our results show that options and short trading are complements rather than substitutes. This result is consistent with the literature demonstrating that relatively few stocks are short sale constrained, which thus limits the need to substitute in the options market.

The second issue we consider is the information provided by the options market. Specifically, given that 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 option markets add information about the equities market. Some evidence suggests that the options market is redundant. Stephan and Whaley (1990) and Chan, Chung, and Johnson (1993) use intraday data to show that the equities market leads the options market and that the options market does not add additional information. Muravyev, Pearson, and Broussard (2012) also use intraday data to demonstrate the option market offers no additional price discovery beyond what is available in the equities market. Similarly, Chan, Chung, and Fong (2002) show that stock volume, but not option volume, has predictive power for returns, suggesting the options market does not contain any information not already reflected in the market for the underlying securities.

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) either theoretically show or empirically demonstrate the option market is non-redundant to the equities market, and contains information not contemporaneously incorporated in the stock market.[1] Consequently, the options market is thought to provide price discovery that is incremental to that of the underlying equities market.

Many studies provide evidence for option market non-redundancy by showing the option market has the ability to predict future stock returns, and thus contains informed traders not acting in the equities market. For example, Easley, O'Hara, and Srinivas (1998) demonstrate that buyer-initiated versus seller initiated option volume is able to predict stock returns. Similarly, Pan and Poteshman (2006) provide evidence that initiated put volume relative to call volume has

[1] 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.

explanatory power over future stock returns, and that option traders possess nonpublic information. Roll, Schwartz, and Subrahmanyam (2010) and Johnson and So (2012) demonstrate the return predictability of option to stock trading volume ratio also suggests options traders are informed. Chakravarty, Gulen, and Mayhew (2004) find that the average contribution of the options market to price discovery is about 17%. Ofek, Richardson, and Whitelaw (2004), Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing, Zhang, and Zhao (2010) demonstrate option put-call parity or implied volatilities can predict future stock returns.[2]

Related to the issue of redundancy is the third issue addressed in our paper. Specifically, we ask whether short sellers or option traders are relatively more informed. While there is some debate about the information contained in the options market as discussed above, extant literature makes a good case for short sellers being sophisticated investors and superior processors of information. 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, Hutton, Meulbroek, and Sloan (2001) demonstrate short sellers trade against firms whose fundamental ratios do not support their price. Drake, Rees, and Swanson (2011) find similar evidence of short sellers trading based on firm fundamentals, and show short sellers outperform analysts in this regard.[3] Diether, Lee, and Werner (2009) also find short sellers are contrarian with respect to momentum, selling stock after past positive returns.

[2] Additionally, Patell and Wolfson (1981), Barone-Adesi, Brown, and Harlow (1994), Levy and Yoder (1993), Jayaraman, Frye, and Sabherwal (2001), Cao, Chen, and Griffin (2005), and Jin, Livnat, and Zhang (2012) find that option markets can predict the content of earnings announcements as well as corporate events such as merger announcements and probability of merger completion. Furthermore, Cao et al. find option volume imbalances are proportional to takeover premiums.

[3] Many other studies find short sellers profit from accounting-based information, establishing them as advanced information processors, including Desai, Krishnamurthy, and Venkataraman (2006).

Several studies, such as Asquith and Meulbroek (1995), Jayaraman, Frye, and Sabherwal (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Boehmer, Jones, and Zhang (2008), and Diether, Lee, and Werner (2009), show an inverse relation between short sales and future returns, indicating short sellers can predict stock returns. Furthermore, Safieddine and Wilhelm (1996), Christophe, Ferri, and Hsieh (2010), Karpoff and Lou (2010), and Liu and Swanson (2012) find short sellers anticipate events such as earnings surprises, financial misconduct, analyst downgrades, credit rating downgrades, mergers, repurchases, and seasoned equity offerings. Christophe, Ferri, and Hsieh (2010) and Henry and Koski (2010) suggest short sellers are "tipped off" or engage in price manipulation, but Drake, Rees, and Swanson (2011), Blau and Pinegar (2012), and Engelberg, Reed, and Ringgenberg (2012) find short sellers are skilled at information processing, and Boehmer and Wu (2012) demonstrate short selling is contrarian and important to the price discovery process.

While studies such as Chan, Chung, and Fong (2002) and Muravyev, Pearson, and Broussard (2012) show price discovery occurs in the equities market and not necessarily in the options market, they do not explore short sales. We hypothesize that, if option 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 option 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.

The results of our dynamic analysis 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 Roll et al.'s (2011) ratio of dollar option volume to dollar stock volume, which includes important price information about options, 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 short traders are generally backward-looking and respond to past negative return performance with increased short activity (e.g., momentum traders). 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 option traders are relatively 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 II discusses the data and variables. Section III discusses how to investigate whether options and short trading are complements or substitutes and how to test whether short traders and option traders are informed traders based on potential information asymmetry between these traders and other investors. Section IV presents the empirical findings. Section V concludes the paper.

II. Data and Methodology

We obtain returns and outstanding shares for Standard and Poor's 500 (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 comes from the NYSE and Nasdaq exchanges, where 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.

Optionmetrics Ivy DB provides the 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.[4] The call ($OIRC_t$) and put ($OIRP_t$) open interest ratios across all call and put options 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

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

recently identified by Roll, Schwartz, and Subrahmanyam (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.[5] 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 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

[5] 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.

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 1996-2009.

III. Empirical Methods

To address the issues discussed above, we develop an empirical framework that helps us test whether short selling and option trading are complements or substitutes and whether short sellers and option traders are informed traders.

3.1. Short sales and option 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:

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

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

In equations (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).

3.2. 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 option traders) and other uninformed investors. In such a case, short-sale (or option trading) decisions may contain (or convey) new information about future stock returns. In fact, some short-sale (or option 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 option 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 option 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 option traders) use in short sales (or option trading).[6] Our model is very useful because it provides a regression model that tests the predictive power of short sales (or option trading) under potential information asymmetry.

[6] 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)).

Here 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 (pages 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:

$$R_t = (1 - \lambda L)\, u_t, \qquad |\lambda| < 1.0\,, \tag{3}$$

where R_t is the stock return at time t, L is the lag (or backshift) operator (i.e., $L^n R_t = R_{t-n}$), and u_t is white noise with $\mathrm{var}(u_t) = \sigma_u^2$. The autocovariance functions (ACFs) for this MA(1) return process are:[7]

$$\mathrm{var}(R_t) = (1 + \lambda^2)\, \sigma_u^2,$$

$$\mathrm{cov}(R_t, R_{t-1}) = - \lambda\, \sigma_u^2,$$

$$\mathrm{cov}(R_t, R_{t-k}) = 0, \text{ for } k \geq 2. \tag{4}$$

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

$$R_t = (1 - \lambda^{-1} L)\, v_t, \qquad |\lambda| < 1.0\,, \tag{5}$$

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

[7] 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.

$$\mathrm{var}(R_t) = (1 + \lambda^{-2})\, \sigma_v^2,$$

$$\mathrm{cov}(R_t, R_{t-1}) = - \lambda^{-1}\, \sigma_v^2,$$

$$\mathrm{cov}(R_t, R_{t-k}) = 0, \text{ for } k \geq 2. \qquad (6)$$

It is noted that if we set $\sigma_v^2 = \lambda^2 \sigma_u^2$, then the ACFs in (4) and (6) are identical. Since the return process can be identified in practice by the observed ACFs, the identical ACFs imply that stock return processes in (3) and (5) represent the same return process. That is, for a given return process, uninformed investors and informed short sellers (or option traders) may infer different MA(1) processes.[8]

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

$$\sigma_v^2 < \sigma_u^2 . \qquad (7)$$

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 (5) by informed short sellers (i.e., σ_v^2) would be smaller than the corresponding variance of the return process in (3) 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, $\Omega_t = \{R_{t-j}, u_{t-j}, \text{ for } j \geq 0\}$.

[8] The return process in (3) with innovation u_t is an invertible MAR because the root of the determinant of the MAR of R_t is greater than 1 (i.e., det $[1- \lambda z] = 0$, for $z = \lambda^{-1}$). However, the return process with the innovations v_t in (5) is a non-invertible MAR because the root of the determinant is less than 1 (i.e., det $[1- \lambda^{-1} z] = 0$, for $z = \lambda$).

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 (3) and (5):

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

$$v_t = (1-\lambda^{-1} L)^{-1} R_t = -(\lambda L^{-1})(1-\lambda L^{-1})^{-1} R_t = -\sum_{j=1}^{\infty} \lambda^j R_{t+j}. \qquad (8)$$

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.[9]

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:

$$SIR_t = f(v_t) = \sum_{i=0}^{\infty} (\theta_i L^i) v_t = \sum_{i=0}^{\infty} \theta_i v_{t-i}, \text{ with } \sum_{i=0}^{\infty} \theta_i^2 < \infty. \qquad (9)$$

Then, by using v_t in (8), short interest and stock return processes will be related as follows:

[9] 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 (8) backwards, the right-hand side is not square summable.

$$SIR_t = \sum_{i=0}^{\infty} (\theta_i \, L^i) \, v_t \; = \; \sum_{i=0}^{\infty} (\theta_i \, L^i) \, \{ \, (1 - \lambda^{-1} \, L)^{-1} R_t \}$$

$$= \sum_{i=0}^{\infty} (\theta_i \, L^i \,)(- \sum_{j=1}^{\infty} \lambda^j \, R_{t+j}) = \sum_{j=-\infty}^{\infty} \delta_j \, R_{t-j} \, , \qquad (10)$$

where δ_j for j = -∞, …, -2, -1, 0, 1, 2, ….∞ 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.[10]

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:

$$SIR_t = f\,(\,u_t) = \sum_{i=0}^{\infty} (\theta_i \, L^i) \, u_t \; = \; \sum_{i=0}^{\infty} \theta_i u_{t-1}, \quad \text{with } \sum_{i=0}^{\infty} \theta_i^2 < \infty. \qquad (11)$$

Then, by using u_t in (8), uninformed short sales and stock return processes will be related as follows:

$$SIR_t = \sum_{i=0}^{\infty} (\theta_i \, L^i) \, u_t \; = \; \sum_{i=0}^{\infty} (\theta_i \, L^i \,) \, (1 - \lambda \, L)^{-1} R_t$$

$$= \sum_{i=0}^{\infty} (\theta_i \, L^i) \; \{ \sum_{j=0}^{\infty} \lambda^j \, R_{t-j} \; \} \; = \; \sum_{k=0}^{\infty} \delta_k \, R_{t-k}, \qquad (12)$$

[10] In practice, since short sellers do not have perfect foresights, (10) will be

$$SIR_t = \sum_{j=0}^{\infty} \delta_j \, R_{t-j} + E_t [\sum_{j=-\infty}^{-1} \delta_j \, R_{t-j} \,]. \qquad (10)'$$

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.

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.

The equivalence of the two-sided regression in (10) with Granger (1969) causality has been established by Sims (1972, Theorem 2), which we restate in our context:

Proposition 1. Consider the following two-sided regression:

$$SIR_t = \alpha + \sum_{j=-m}^{m} \delta_j \ R_{t-j} + \ \varepsilon_t, \qquad (13)$$

where E(ε_t. R_{t-j}) = 0 for all j (= -m. …-1, 0, 1,… m). If the null hypothesis that all the coefficients of future returns are zero (i.e., δ_j = 0 for all j < 0) is rejected, then SIR_t Granger-causes R_t.

That is, we can use the two-sided regression as a means of testing the predictability of short sales for market returns, and the finding of the predictive power of short sales 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.

IV. Empirical Results

4.1. 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., $RESP_t$), 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. That is, we find $RESP_t$, $RESC_t$, and $RES3_t$ 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.

[Insert Table 1 Here]

4.2. Short sales and option 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. It is possible that options may alleviate short sale constraints and allow investors an alternative (i.e., substitute) method of acting on pessimistic sentiment. However, most stocks are not found to be short sale constrained and pessimistic positions may be taken in both the equities and options market.

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 Section 3.1 with equations (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) Δ OIRP and Δ OPIRC are neither a substitute nor a complement to Δ SIR.
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.

[Insert Table 2 Here]

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

The literature is mixed with respect to the information contained in option trading. Some evidence suggests that options activity is redundant and does not contain information in addition to that found in equities while other evidence suggests that option activity can be used to predict returns. While short sellers are generally considered to be informed, a comparison of the relative information contained by short sellers versus option traders has, to our knowledge, not been addressed. In Table 3 we directly test which of the various groups (short sellers and option traders) are relatively more informed. We do so using Sims (1972) two-sided regression based causality tests in (13).

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

Section 3.2. 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 expectations, higher returns result in lower short interest. *SIR* is found to Granger-cause returns but the direction of the effect is insignificantly positive. The combined results suggest that while short sellers increase short activity in response to lower returns, they are not well informed investors in that their increased short activity does not anticipate lower future returns. Instead, short sellers seem to be backward-looking momentum traders responding to past returns.

In Panel B of Table 3 we find that *RETURN* Granger-causes *OIRP* with a marginally significant positive effect. However, *OIRP* does not Granger-cause returns. This suggests that put activity increases in response to higher returns and put traders are not informed investors as their increased put activity is not in anticipation of significantly lower future returns. Rather, they seem to be backward-looking investors responding to higher recent returns. The positive relation may be due to investors essentially purchasing insurance via put options, locking in recently acquired paper gains.

Panel C of Table 3 shows that *RETURN* Granger-causes *OIRC* with a marginal positive effect, and *OIRC* does not Granger-cause returns. This implies that call activity increases marginally in response to higher returns, and call traders 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.

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.

[Insert Table 3 Here]

4.4. 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, we find *SIR* does not Granger-cause returns, while *OIRP* and *OIRC* Granger-cause returns. *OIRP* (*OIRC*) anticipates positive (negative) stock returns, which suggests both activities are not well informed or that non-market makers are net writers of calls and are informed. Panel B of Table 4 displays results that indicate *RETURN* Granger-causes *SIR* with a marginally 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 increases in response to lower stock returns (i.e., backward-looking activities).

In Panel C of Table 4, we find that *RETURN* Granger-causes *OIRP* with a positive cumulative effect (significant at the 1% 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. While *OIRC* Granger-causes *OIRP* with a negative effect, its net effect is not significant. In Panel D of Table 4, we see that *RETURN* Granger-causes *OIRC* with a marginally significant positive net effect. 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* Granger-causes *RETURN* (i.e., significant joint test) though the net effect is not significant. *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. *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. *SIR* responds to past *RETURN*, but *O/S* does not. Thus, option traders appear to be informed about future stock returns while short sellers are backward-looking.

[Insert Table 4 Here]

4.5. 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 option traders being relatively more informed. In Table 5 we focus on the relation between short interest and option activity to test more directly who more informed traders are between short traders and option traders.

In Panels A and B, we examine which group (i.e., short traders and option traders) is more informed using two-sided regressions. In Panel A, which uses the first differences of the variables in our VECM, *OIRP* and *SIR* Granger cause each other, but the net effect is not significant. 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* Granger cause each other, but the net effect is not significant. This 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, we examine dynamic relations between short interest and option activity using conventional VAR based causality tests. In Panel C of Table 5, *OIRP* helps better predict SIR with a negative net effect (significant at the 1% level) on *SIR*. In Panel D, *SIR* helps better predict *OIRP* with an insignificant net effect on *OIRP*. Overall, for Panels C and D, *OIRP* helps better predict *SIR* with a net significant negative effect on *SIR*.

In Panel E, we examine the ability *OIRC* to predict *SIR*. We find that *OIRC* helps better predict *SIR* with a negative net effect (significant at the 1% level). In Panel F, we examine the ability of *SIR* to predict *OIRC*. We find that *SIR* helps predict *OIRC* with an 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 examine the ability of *O/S* to predict *SIR* and the ability of *SIR* to predict *O/S*, respectively. We do not find a causal relation between *O/S* and *SIR* or between *SIR* and *O/S*. Thus, the evidence suggests that option traders and short traders act independently of one another.

The results of Table 5 consistently 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 either cointegration or both volume and price of options via the O/S measure, there is no longer a significant relation.

[Insert Table 5 Here]

4.6. 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 both *SIR* and *OIRC* help predict *OIRP*, but the 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 conclusions about which group is relatively more informed in this analysis.

[Insert Table 6 Here]

4.7. Robustness

We have conducted a battery of robustness tests. The results are not reported here, but are available upon request. Our robustness checks include: 1) different measures of option open interest, 2) using levels of non-stationary variables, and 3) using index level option volatility spreads. 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. 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 critical.

Finally, 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.

V. Conclusion

We examine the dynamic relation between aggregate returns, short trading, and option activity in the U.S. over the period 1996-2009. Our goal is three-fold: 1) to determine whether short selling and option 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 option 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.

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 responds to past negative return performance with increased short interest. We add to the existing literature by showing aggregate option activity, 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 indicates the options market contains information not present in the equities market. Thus, taking all the evidence together, option 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.

Appendix A – 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

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Table 1.

Unit root tests: sample period, 1996:03 to 2009:12 (Observations 167)

(i) Augmented Dickey-Fuller regression

$$\Delta x_t = a_0 + \alpha x_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta x_{t-i} + v_t$$

(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
RETURNt	-8.762	-6.4823	-5.362	-4.850	-11.318	-11.292	-11.309	-11.344
SIR_t	-1.348	-1.355	-1.447	-1.091	-1.478	-1.483	-1.497	-1.471
$OIRP_t$	-0.831	-0.485	-0.362	-0.363	-0.775	-0.686	-0.587	-0.532
$OIRC_t$	-1.112	-0.787	-0.637	-0.629	-1.012	-0.947	-0.853	-0.790
O/S_t	-4.578	-3.737	-3.284	-2.859	-4.634	-4.475	-4.326	-4.217
$RESP_t$	-3.744	-3.850	-3.309	-3.007	-3.422	-3.554	-3.531	-3.458
$RESC_t$	-3.877	-3.941	-3.347	-2.857	-3.442	-3.584	-3.566	-3.469
$RES3_t$	-3.651	-3.774	-3.263	-3.035	-3.393	-3.518	-3.494	-3.435
RESPCt	-2.362	-2.399	-2.111	-2.601	-2.625	-2.648	-2.601	-2.708

Note:
$RETURN_t$ = 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 $OIRC_t$.
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).

Table 2. Complements versus substitutes:

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
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)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	-0.0066	t = -0.4238	0.6717
$\Delta SIR_t = \alpha + \sum_{j=1}^{3}\alpha_j\ \Delta SIR_{t-j} + \sum_{j=0}^{3}\beta_j\ \Delta OIRC_{t-j} + b * RESC_{t-1}$ (1)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	-0.0082	t = -0.6519	0.5145
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3}\alpha_j\ \Delta OIRP_{t-j} + \sum_{j=0}^{3}\beta_j\ \Delta SIR_{t-j} + b * RESP_{t-1}$ (2)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	4.9969	t =1.8559	0.0635
$\Delta OIRC_t = \alpha + \sum_{j=1}^{3}\alpha_j\ \Delta OIRC_{t-j} + \sum_{j=0}^{3}\beta_j\ \Delta SIR_{t-j} + b * RESC_{t-1}$ (2)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	5.1121	t =1.8628	0.0625
$\Delta OIRP_t = \alpha + \sum_{j=1}^{3}\alpha_j\ \Delta OIRP_{t-j} + \sum_{j=0}^{3}\beta_j\ \Delta OIRC_{t-j} + b * RESPC_{t-1}$ (2)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	0.9140	t =6.7472	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)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	1.2512	t =6.4552	0.0000
$SIR_t = \alpha + \sum_{j=1}^{3}\alpha_j\ SIR_{t-j} + \sum_{j=0}^{3}\beta_j\ OIRP_{t-j}$ (1)			
$H_0: \sum_{j=0}^{3}\beta_j = 0.$	0.0055	t = 2.3159	0.0206

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level
$SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \, SIR_{t-j} + \sum_{j=0}^{3} \beta_j \, OIRC_{t-j}$ (1)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	0.0054	t = 2.7182	0.0066
$OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j \, OIRP_{t-j} + \sum_{j=0}^{3} \beta_j \, SIR_{t-j}$ (2)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	1.5947	t =2.6626	0.0078
$OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j \, OIRC_{t-j} + \sum_{j=0}^{3} \beta_j \, SIR_{t-j}$ (2)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	1.5744	t =2.6789	0.0074
$OIRP_t = \alpha + \sum_{j=1}^{3} \alpha_j \, OIRP_{t-j} + \sum_{j=0}^{3} \beta_j \, OIRC_{t-j}$ (2)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	0.0732	t =2.0786	0.0377
$OIRC_t = \alpha + \sum_{j=1}^{3} \alpha_j \, OIRC_{t-j} + \sum_{j=0}^{3} \beta_j \, OIRP_{t-j}$ (2)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	0.0967	t =2.2293	0.0258
$\Delta SIR_t = \alpha + \sum_{j=1}^{3} \alpha_j \, \Delta SIR_{t-j} + \sum_{j=0}^{3} \beta_j \, O/S_{t-j}$ (1)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	0.0012	t = 0.7448	0.4582
$O/S_t = \alpha + \sum_{j=1}^{3} \alpha_j \, O/S_{t-j} + \sum_{j=0}^{3} \beta_j \, \Delta SIR_{t-j}$ (2)			
$H_0: \sum_{j=0}^{3} \beta_j = 0.$	-11.4987	t =-1.2915	0.1965

Table 3

Tests of the information content using Sims (1972) causality tests: 1996:04 to 2009:12 (Observations 164)

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level

Sims (1972) causality test for sample period, **1996:03 to 2009:12 (Observations 167)**

Panel A: ΔSIR_t **on *RETURN***

$$\Delta SIR_t = \alpha + \sum_{j=-3}^{3} \gamma_j \,\mathrm{Re}turn_{t-j} \;, \qquad (13)$$

$H_0: \ \gamma_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 13.0547	0.0045
$H_0: \ \sum_{j=1}^{3} \gamma_j = 0.$	-0.0065	t = -2.7721	0.0056
$H_0: \ \gamma_j = 0$ for j = -1, -2, -3,		χ^2 (3) = 10.1286	0.0175
$H_0: \ \sum_{j=-1}^{-3} \gamma_j = 0.$	0.0036	t = 1.4798	0.1389

Panel B: $\Delta OIRP$ **on *RETURN***

$$\Delta OIRP_t = \alpha + \sum_{j=-3}^{3} \gamma_j \,\mathrm{Re}turn_{t-j} \;, \qquad (13)$$

$H_0: \ \gamma_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 8.4706	0.0372
$H_0: \ \sum_{j=1}^{3} \gamma_j = 0.$	0.0637	t = 1.5413	0.1232
$H_0: \ \gamma_j = 0$ for j = -1, -2, -3,		χ^2 (3) = 3.7415	0.2908
$H_0: \ \sum_{j=-1}^{-3} \gamma_j = 0.$	-0.0200	t = -0.6864	0.4925

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level

Sims (1972) causality test for sample period, **1996:04 to 2009:12 (Observations 166)**

Panel C: $\Delta OIRC$ **on *RETURN***

$$\Delta OIRC_t = \alpha + \sum_{j=-3}^{3} \gamma_j \, \mathrm{Re}turn_{t-j} \,, \qquad (13)$$

H_0: $\gamma_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 6.4240	0.0927
H_0: $\sum_{j=1}^{3} \gamma_j = 0.$	0.0674	t = 1.3734	0.1696
H_0: $\gamma_j = 0$ for j = -1, -2, -3,		χ^2 (3) = 4.9826	0.1731
H_0: $\sum_{j=-1}^{-3} \gamma_j = 0.$	-0.0534	t = -1.3985	0.1620

Panel D: O/S on *RETURN*

$$O/S_t = \alpha + \sum_{j=-3}^{3} \gamma_j \, \mathrm{Re}turn_{t-j} \,, \qquad (13)$$

H_0: $\gamma_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 12.1652	0.0068
H_0: $\sum_{j=1}^{3} \gamma_j = 0.$	-0.4492	t = -3.4187	0.0006
H_0: $\gamma_j = 0$ for j = -1, -2, -3,		χ^2 (3) = 26.5361	0.0000
H_0: $\sum_{j=-1}^{-3} \gamma_j = 0.$	-0.7706	t =-5.0421	0.0000

Table 4

Tests of the information content using causality tests: 1996:04 to 2009:12 (Observations 164)

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level
Panel A: *RETURN* regression			
$\mathrm{Re}turn_t = \gamma + \sum_{j=1}^{3} a_j \mathrm{Re}turn_{t-j} + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRC_{t-j}$,			
H_0 : $b_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 3.8251	0.2810
H_0 : $\sum_{j=1}^{3} b_j = 0.$	7.1230	t = 0.9761	0.3290
H_0 : $c_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 7.3732	0.0609
H_0 : $\sum_{j=-1}^{-3} c_j = 0.$	3.3378	t = 2.2324	0.0256
H_0 : $d_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 8.1579	0.0429
H_0 : $\sum_{j=-1}^{-3} d_j = 0.$	-3.2996	t = -2.5305	0.0114
Panel B: SIR regression			
$\Delta SIR_t = \gamma + \sum_{j=1}^{3} a_j \Delta SIR_{t-j} + \sum_{j=1}^{3} b_j \mathrm{Re}turn_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRC_{t-j}$,			
H_0 : $b_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 11.8667	0.0079
H_0 : $\sum_{j=1}^{3} b_j = 0.$	-0.0046	t = -1.6554	0.0978
H_0 : $c_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 1.8499	0.6041
H_0 : $\sum_{j=-1}^{-3} c_j = 0.$	0.0159	t = 0.4686	0.6394
H_0 : $d_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 3.1210	0.3733
H_0 : $\sum_{j=-1}^{-3} d_j = 0.$	-0.0380	t = -1.4154	0.1570

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level

Panel C: OIRP regression

$$\Delta OIRP_t = \gamma + \sum_{j=1}^{3} a_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} b_j \operatorname{Re}turn_{t-j} + \sum_{j=1}^{3} c_j \Delta SIR_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRC_{t-j} \,,$$

$H_0: \; b_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 11.8828	0.0078
$H_0: \; \sum_{j=1}^{3} b_j = 0.$	0.0852	t = 2.3684	0.0179
$H_0: \; c_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 10.1624	0.0172
$H_0: \; \sum_{j=-1}^{-3} c_j = 0.$	4.1973	t = 1.8175	0.0691
$H_0: \; d_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 8.0929	0.0441
$H_0: \; \sum_{j=-1}^{-3} d_j = 0.$	-0.0590	t = -0.1508	0.8801

Panel D: OIRC regression

$$\Delta OIRC_t = \gamma + \sum_{j=1}^{3} a_j \Delta OIRC_{t-j} + \sum_{j=1}^{3} b_j \operatorname{Re}turn_{t-j} + \sum_{j=1}^{3} c_j \Delta SIR_{t-j} + \sum_{j=1}^{3} d_j \Delta OIRP_{t-j} \,,$$

$H_0: \; b_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 8.3889	0.0386
$H_0: \; \sum_{j=1}^{3} b_j = 0.$	0.0729	t = 1.8089	0.0705
$H_0: \; c_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 12.5125	0.0058
$H_0: \; \sum_{j=-1}^{-3} c_j = 0.$	3.6938	t = 1.3879	0.1652
$H_0: \; d_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 0.9037	0.8245
$H_0: \; \sum_{j=-1}^{-3} d_j = 0.$	-0.0598	t = -0.1006	0.9199

H$_0$ (null hypothesis)	.	Chi-square statistic	Significance level
H$_0$ (null hypothesis)	sum of coeff.	t-statistic	Significance level

Panel E: *RETURN* regression

$$\mathrm{Re}turn_t = \gamma + \sum_{j=1}^{3} a_j \,\mathrm{Re}turn_{t-j} + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} c_j \; O/S_{t-j} \;,$$

H$_0$: $b_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 7.4290	0.0594
H$_0$: $\sum_{j=1}^{3} b_j = 0.$	10.4694	t = 1.4203	0.1555
H$_0$: $c_j = 0$ for j = 1, 2, 3,		χ^2 (3) =15.9600	0.0012
H$_0$: $\sum_{j=-1}^{-3} c_j = 0.$	- 0.2096	t =-3.2978	0.0010

Panel F: SIR regression

$$\Delta SIR_t = \gamma + \sum_{j=1}^{3} a_j \Delta SIR_{t-j} + \sum_{j=1}^{3} b_j \,\mathrm{Re}turn_{t-j} + \sum_{j=1}^{3} c_j \; O/S_{t-j} \;,$$

H$_0$: $b_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 15.7666	0.0013
H$_0$: $\sum_{j=1}^{3} b_j = 0.$	-0.0074	t = -3.0775	0.0021
H$_0$: $c_j = 0$ for j = 1, 2, 3,		χ^2 (3) = 2.4360	0.4870
H$_0$: $\sum_{j=-1}^{-3} c_j = 0.$	-0.0008	t = -0.4982	0.6183

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level

Panel G: O/S regression

$$O/S_t = \gamma + \sum_{j=1}^{3} a_j O/S_{t-j} + \sum_{j=1}^{3} b_j \mathrm{Re}turn_{t-j} + \sum_{j=1}^{3} c_j \Delta SIR_{t-j},$$

H_0: $b_j = 0$ for j = 1, 2, 3,		$\chi^2(3) = 2.3216$	0.5083
H_0: $\sum_{j=1}^{3} b_j = 0.$	- 0.0144	t = -0.1146	0.9088
H_0: $c_j = 0$ for j = 1, 2, 3,		$\chi^2(3) = 5.1887$	0.1585
H_0: $\sum_{j=-1}^{-3} c_j = 0.$	-16.0931	t = -2.2349	0.0254

Table 5

Tests of the information content using Sims (1972) causality tests: 1996:04 to 2009:12 (Observations 164)

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level

Sims (1972) causality test for sample period, 1996:03 to 2009:12 (Observations 167)

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 (4) = 12.4043	0.0146
$H_0: \ \sum_{j=1}^{3} \gamma_j = 0.$	-0.0120	t = -1.0040	0.3154
$H_0: \ \gamma_j = 0$ for j = -1, -2, -3, and b = 0		χ^2 (4) = 12.5855	0.0135
$H_0: \ \sum_{j=-1}^{-3} \gamma_j = 0.$	0.0136	t = 0.9548	0.3397

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 (4) = 10.2756	0.0360
$H_0: \ \sum_{j=1}^{3} \gamma_j = 0.$	-0.0143	t = -1.3628	0.1729
$H_0: \ \gamma_j = 0$ for j = -1, -2, -3, and b = 0		χ^2 (4) = 10.7714	0.0293
$H_0: \ \sum_{j=-1}^{-3} \gamma_j = 0.$	0.0077	t = 0.6815	0.4956

H$_0$ (null hypothesis)	.	Chi-square statistic	Significance level
H$_0$ (null hypothesis)	sum of coeff.	t-statistic	Significance level
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 (4) = 8.8444	0.0651
H$_0$: $\sum_{j=1}^{3} \gamma_j = 0$.	-0.0358	t = -2.6707	0.0076
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 (4) = 9.7231	0.0454
H$_0$: $\sum_{j=1}^{3} \gamma_j = 0$.	1.9720	t = 0.7675	0.4428
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 (4) = 11.1793	0.0246
H$_0$: $\sum_{j=1}^{3} \gamma_j = 0$.	-0.0336	t = -2.9784	0.0029

H$_0$ (null hypothesis)	.	Chi-square statistic	Significance level
H$_0$ (null hypothesis)	sum of coeff.	t-statistic	Significance level

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$_0$: γ_j = 0 for j = 1, 2, 3,		χ^2 (4) = 11.3662	0.0227
H$_0$: $\sum_{j=1}^{3} \gamma_j = 0.$	1.6857	t = 0.6201	0.5352

Panel G: Δ SIR 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$_0$: γ_j = 0 for j = 1, 2, 3,		χ^2 (3) = 1.1289	0.7701
H$_0$: $\sum_{j=1}^{3} \gamma_j = 0.$	0.0007	t = 0.4477	0.6544

Panel H: O/S on Δ SIR

$$O/S_t = \alpha + \sum_{j=1}^{3} b_j \, O/S_{t-j} + \sum_{j=1}^{3} \gamma_j \Delta SIR_{t-j},$$

H$_0$: γ_j = 0 for j = 1, 2, 3,		χ^2 (3) = 4.5969	0.2038
H$_0$: $\sum_{j=1}^{3} \gamma_j = 0.$	-15.4969	t = -2.1111	0.0348

Table 6

Tests of the information content using causality tests: 1996:05 to 2009:12 (Observations 164)

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	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 (4) = 4.9524	0.2992
$H_0:\ \sum_{j=1}^{3} b_j = 0.$	0.0045	t = 0.1302	0.8964
$H_0:\ c_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 6.2742	0.1796
$H_0:\ \sum_{j=1}^{3} c_j = 0.$	-0.0376	t = -1.3820	0.1670

Panel B: OIRP regression

$$\Delta OPENP_t = \gamma + \sum_{j=1}^{3} a_j \Delta OIRP_{t-j} + \sum_{j=1}^{3} b_j \Delta SIR_{t-j} + \sum_{j=1}^{3} c_j \Delta OIRC_{t-j} + d * RES3_{t-1},$$

$H_0:\ b_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (4) = 10.5354	0.0323
$H_0:\ \sum_{j=1}^{3} b_j = 0.$	2.0320	t = 0.8230	0.4105
$H_0:\ c_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 8.8432	0.0651
$H_0:\ \sum_{j=1}^{3} c_j = 0.$	-0.1157	t = -0.2577	0.7967

H_0 (null hypothesis)	.	Chi-square statistic	Significance level
H_0 (null hypothesis)	sum of coeff.	t-statistic	Significance level

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 (4) = 11.3830	0.0226
H_0: $\sum_{j=1}^{3} b_j = 0.$	1.8091	t = 0.6594	0.5097
H_0: $c_j = 0$ for j = 1, 2, 3, and d = 0		χ^2 (3) = 1.5640	0.8152
H_0: $\sum_{j=1}^{3} c_j = 0.$	0.0987	t = 0.1579	0.8745