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Short Selling and the Price Discovery Process

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We show that stock prices are more accurate when short sellers are more active. First, in a large panel of NYSE-listed stocks, intraday informational efficiency of prices improves with greater shorting flow. Second, at monthly and annual horizons, more shorting flow accelerates the incorporation of public information into prices. Third, greater shorting flow reduces post-earnings-announcement drift for negative earnings surprises. Fourth, short sellers change their trading around extreme return events in a way that aids price discovery and reduces divergence from fundamental values. These results are robust to various econometric specifications, and their magnitude is economically meaningful. (JEL G14)

The consequences of short selling for share prices, market quality, and information flow are still fervently debated by academics, securities market regulators, and politicians. The informational efficiency of prices, a public good, is a key attribute of capital markets that can have significant implications for the real economy.¹ Short sellers account for more than 20% of trading volume and are generally regarded as traders with access to value-relevant information (Boehmer, Jones, and Zhang 2008). This suggests that they play an important role in the price discovery process. However, being informed does not necessarily imply that their trading instantaneously impounds this

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¹ More efficient stock prices more accurately reflect a firm's fundamentals and can guide firms in making better-informed investment and financing decisions. Related theoretical work focusing on the link between the informativeness of market prices and corporate decisions includes, among others, Tobin (1969), Dow and Gorton (1997), Subrahmanyam and Titman (2001), and Goldstein and Guembel (2008). Also related are recent empirical studies on seasoned equity offerings (Giammarino et al. 2004), mergers and acquisitions (Luo 2005), and investments in general (Chen, Goldstein, and Jiang 2007).

information into prices—in fact, informed traders often have incentives to trade in a way that minimizes information leakage. In this article, we use daily data on short-selling flow and various dimensions of informational efficiency to systematically quantify the effect of daily short-selling flow on the price discovery process.

Financial theory takes different views on short sellers and the consequences of their trading decisions on price discovery and, more generally, on market quality. In some models, short sellers are rational informed traders who promote efficiency by moving mispriced securities closer to their fundamentals (see, e.g., Diamond and Verrecchia 1987). In other models, short sellers follow manipulative and predatory trading strategies that result in less informative prices (Goldstein and Guembel 2008) or cause overshooting of prices (Brunnermeier and Pedersen 2005). Most empirical studies suggest that short sellers are informed traders. Using either monthly short interest data (see, e.g., Asquith and Meulbroek 1995; Dechow et al. 2001; Desai et al. 2002; Asquith, Pathak, and Ritter 2005) or shorting flow data (see, e.g., Christophe, Ferri, and Angel 2004; Boehmer, Jones, and Zhang 2008; Diether, Lee, and Werner 2008), these authors document that short sellers have value-relevant information and suggest that their trading helps correct overvaluation.

Our article connects to this point. In line with previous work, we agree that short sellers' information will eventually be incorporated into prices; going beyond previous work, we use higher-frequency daily data on short-selling flow to characterize more precisely how and when short sellers impact price discovery. Most prior work uses monthly short interest reports to examine whether short sellers anticipate future returns or changes in firm fundamentals (see, e.g., Dechow et al. 2001; Karpoff and Lou 2010; Henry, Kisgen, and Wu 2011). We take a different approach by directly focusing on short sellers' daily trading activity and its impact on price discovery at different horizons. This allows us to systematically examine whether short sellers' information is incorporated into prices and how quickly this takes place. Our daily flow data are more appropriate for this analysis than are monthly snapshots of short interest data when short sellers adopt short-term trading strategies. Indeed, recent empirical evidence suggests that many short sellers are active short-term traders. Between November 1998 and October 1999, Reed (2007) finds that the median duration of a position in the equity lending market is three days, and the mode is only one day. Diether, Lee, and Werner (2008) estimate an average days-to-cover ratio of four to five days for a shorted stock in 2005. These findings indicate that a large portion of recent short-selling activity is short-term and indeed often limited to intraday horizons. Daily shorting flow data allow us to capture the effect of these shorting activities on prices and facilitate a more detailed analysis than monthly short interest data.

We use four distinct approaches when analyzing the effect of shorting on informational efficiency. First, following Boehmer and Kelley (2009), we construct transaction-based high-frequency measures of efficiency. Second,

we adopt Hou and Moskowitz's (2005) lower-frequency price-delay measure, an estimate of how quickly prices incorporate public information. Third, we use the well-established post-earnings-announcement drift anomaly (see Ball and Brown 1968) as a measure of inefficiency and test whether short sellers influence its magnitude. Fourth, we examine short selling around large price movements and price reversals. By design, these four approaches are complementary in their assumptions and allow us to examine the effects of short selling on efficiency from different perspectives. Together, analyzing the influence of short selling along those four distinct dimensions of informational efficiency provides a detailed and integrated view on the role short sellers play in equity markets.

Each of the four approaches suggests that short sellers improve the informational efficiency of prices. First, more shorting flow reduces the deviation of intraday transaction prices from a random walk, so more shorting makes prices more efficient. Second, more shorting flow is associated with shorter Hou-Moskowitz price delays, suggesting that prices incorporate public information faster when short sellers are more active. Third, for the most negative quartile of earnings surprises, an above-median increase in shorting immediately after the earnings announcement eliminates the drift. Fourth, we find no evidence that short sellers exacerbate large negative price shocks. Conversely, their trading patterns seem to facilitate more accurate pricing even on extreme return days. All these results are robust to different econometric methods and specifications, and as we discuss in Section 7, they are difficult to explain by reverse causality. Further analysis reveals that the efficiency-enhancing effect of short selling is economically meaningful. Overall, these findings suggest that short sellers play a critical role in facilitating rational price discovery, a major function of capital markets, along several dimensions.

Our article is related to several earlier studies on short selling. We complement earlier work by Dechow et al. (2001), Desai et al. (2002), Hirshleifer, Teoh, and Yu (2011), and others that examines the relation between monthly short interest and variables related to firm fundamentals. These studies typically benefit from long monthly time series. Our shorting flow data cover only three years, but we can zoom in on the daily horizon and directly evaluate the impact that shorting has on prices. As Richardson (2003) points out, higher data frequency is important in identifying the impact of short selling on firm fundamentals. We also complement earlier work by Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2008), who find that daily shorting flows predict returns over horizons up to several months. Both of these sets of studies suggest that the presence of short sellers is linked to some correction of overvaluation. However, neither focuses on the questions of when exactly short selling affects prices or how quickly their information is incorporated into prices. Our first contribution is to complement these studies by focusing directly on the link between daily shorting flows and four different measures

of informational efficiency. We show that shorting flow indeed makes prices more efficient and that this process begins at intraday horizons.

Our study is also related to prior work on short-selling constraints. Proxies for shorting constraints include indicators for the practice and prohibition of short selling across equity markets (Bris, Goetzmann, and Zhu 2007), addition/removal of short-sale restrictions in certain stocks in Hong Kong (Chang, Cheng, and Yu 2007), loan rates from a large U.S. security lender in the late 1990s (Reed 2007), and data on share lending supply and borrowing fees from U.S. and other equity markets (Saffi and Sigurdsson 2011). Focusing on variation in shorting constraints and directly linking short sellers' actual trading decisions to price efficiency are complementary approaches, and the latter allows us to examine the consequences of short sellers' decisions more directly.

Our finding that short sellers enhance efficiency around earnings announcements informs the growing body of literature on post-earnings-announcement drift (initially documented in Ball and Brown 1968). Although there is mounting evidence that post-earnings-announcement drift (PEAD) is one of the more persistent anomalies in financial markets, empirical work on shorting behavior in this context is quite limited. Using monthly short interest data, Cao et al. (2007) find relatively weak evidence that short sellers reduce drift, but Lasser, Wang, and Zhang (2010) argue that short interest is not related to PEAD in the expected manner. Even with intraday shorting flows, Zheng (2009) finds no evidence that short sellers affect PEAD. Berkman and McKenzie (2012) find that short selling (proxied by loaned shares in the equity lending market) increases after negative earnings shocks but conclude that it does not remove long-term PEAD measured over the quarter following the earnings announcement. We contribute detailed daily evidence to this debate. Consistent with Berkman and McKenzie (2012), we find that shorting increases after negative earnings surprises. Boehmer, Jones, and Zhang (2008) show that the ability of daily short selling to predict future returns dissipates roughly one month after portfolio formation. Thus, short sellers' ability to exploit PEAD should be strongest during the month after the earnings announcement. We find that short selling eliminates PEAD over this horizon in the stocks with negative surprises where short sellers are most active. Overall, these tests also benefit from the daily nature of our data on shorting flows, which allows us to create more powerful tests than would be possible based on monthly short interest reports. Different from the above studies, our new result in this respect is that the activity of short sellers eliminates PEAD at least in some stocks, and this happens fairly quickly, further supporting the positive role of short sellers in promoting efficient pricing.

Finally, our analysis provides important guidance for current worldwide debates regarding the optimal regulation of short selling.² Our article

² Anecdotal evidence indeed goes both ways. Jim Chanos, president of Kynikos Associates (the largest fund specializing in short selling), is best known for being one of the first to spot problems with Enron. However,

contributes to these debates by systematically highlighting how short sellers help increase market quality and illustrating specific ways in which this occurs.

The remainder of the article is organized as follows. Section 1 describes the data and our sample. Section 2 introduces our measures of relative informational efficiency. Section 3 analyzes the relation between short selling and high-frequency measures of efficiency, whereas Section 4 looks at the relation between shorting and low-frequency measures of efficiency. In Section 5, we describe our event-based analysis that relates post-earnings-announcements drift to shorting activity, and in Section 6, we examine short selling around extreme return events. In Section 7, we describe several robustness tests and provide some evidence on causality. Section 8 concludes the article.

1. Data and Sample

The shorting flow data used in this article are published by the NYSE under the Regulation SHO pilot program and are available from January 2005 through June 2007.³ We augment the shorting data by identical, proprietary data obtained from the NYSE that cover the remaining six months of 2007. For each trade, our data include the size of the portion transacted by short sellers, if any. We aggregate the intraday shorting flow that is executed during normal trading hours into daily observations. This sample is limited to a three-year period, but the daily frequency of these flow data allows for more powerful and more accurate tests than those constructed from the monthly short interest data that are used in many of the earlier studies.

We match the daily shorting flow data with the Center for Research in Security Prices (CRSP) database to obtain daily returns, consolidated trading volume, closing prices, and shares outstanding. We include only domestic common stocks (share codes 10 and 11) in the analysis but exclude Berkshire Hathaway Class A and B shares, which are priced around \$3,000 and near \$100,000, respectively, during the sample period. We compute daily liquidity and price efficiency measures from the NYSE's Trades and Quotes (TAQ) data. On an average day, our final sample covers 1,361 stocks.

2. Measuring Price Discovery

We employ four different approaches to measure how efficiently prices incorporate information. First, our most powerful tests focus on high-frequency

some high-profile lawsuits, including Biovail, a Canadian pharmaceutical company suing hedge fund SAC, and Overstock.com, suing Rocker Partners, accuse short sellers of manipulating their stock prices.

³ Regulation SHO initiated by the SEC aims to "study the effects of relatively unrestricted short selling on market volatility, price efficiency, and liquidity" (see Regulation SHO-Pilot Program, April 19, 2005, at www.sec.gov/spotlight/shopilot.htm).

measures of the relative informational efficiency of prices. We measure how closely transaction prices move relative to a random walk and conduct tests at the daily frequency to relate these measures to short-selling flow. Second, we use a longer-horizon measure based on daily and weekly returns. These tests consider the speed with which public information is incorporated into prices over horizons ranging from one month to one year. Third, we exploit the well-documented post-earnings-announcement drift to study the effect of short selling in an event-based context. Fourth, we identify unusually large price changes that are later reversed, and we look at short selling around these changes. Extreme price movements are useful in evaluating the motivation for short selling, because they shed light on whether short sellers trade with the intention to exacerbate or reduce and reverse large price declines.

2.1 High-frequency informational efficiency

We use two different measures to capture the relative efficiency of transaction prices—the pricing error as suggested in Hasbrouck (1993) and the absolute value of intraday return autocorrelations. Both measures are computed from intraday transactions or quote data, and both capture temporary deviations from a random walk (see Boehmer and Kelley 2009). Recent empirical evidence in Chordia, Roll, and Subrahmanyam (2005) supports this short-term view. Their analysis suggests that “astute traders” monitor the market intently and most information is incorporated into prices within 30 minutes through their trading activities. As a result, transaction-based efficiency measures capture temporary deviations from fundamental values well.

We follow Hasbrouck (1993) and Boehmer and Kelley (2009) in computing pricing errors (see the Appendix for details). We decompose the observed (log) transaction price, p_t , into an efficient price (random walk) component, m_t , and a stationary component, the pricing error s_t . The efficient price is assumed to be nonstationary and is defined as a security’s expected value conditional on all available information, including public information and the portion of private information that can be inferred from order flow. The pricing error, which measures the temporary deviation between the actual transaction price and the efficient price, reflects information-unrelated frictions in the market (such as price discreteness, inventory control effects, and other transient components of trade execution costs). To compute the pricing error, we use all trades and execution prices of a stock. We estimate a vector autoregression (VAR) model to separate changes in the efficient price from transient price changes. Because the pricing error is assumed to follow a zero-mean covariance-stationary process, its dispersion, $\sigma(s)$, is a measure of its magnitude. In our empirical analysis, we standardize $\sigma(s)$ by the dispersion of intraday transaction prices, $\sigma(p)$, to control for cross-sectional differences in price volatility. Henceforth, this ratio $\sigma(s)/\sigma(p)$ is referred to as the “pricing error” for brevity. To reduce the

influence of outliers, the dispersion of the pricing error is required to be less than dispersion of intraday transaction prices.⁴

Our second short-term measure of relative price efficiency is the absolute value of quote midpoint return autocorrelations. The intuition is that if the quote midpoint is the market's best estimate of the equilibrium value of the stock at any point in time, an efficient price process implies that quote midpoints follow a random walk. Therefore, quote midpoints should exhibit less autocorrelation in either direction and a smaller absolute value of autocorrelation indicates greater price efficiency. To estimate quote midpoint return autocorrelations, we choose a thirty-minute interval (results are qualitatively identical for five- and ten-minute return intervals) based on the results from Chordia, Roll, and Subrahmanyam (2005). We use $|\text{AR30}|$ to denote the absolute value of this autocorrelation.

In the context of price discovery, pricing errors are easier to interpret than autocorrelations, because only pricing errors differentiate between information-related and information-unrelated price changes. By construction, pricing errors only attribute information-unrelated price changes to deviations from a random walk, whereas autocorrelations incorporate all price changes. For example, splitting a large order by an informed trader would produce zero pricing error because prices change to reflect information from the informed order flow, but it would generate a positive autocorrelation. As price adjustments due to new information are not reflections of inefficiencies, pricing errors are a more sensible measure of the relative informational efficiency of prices.

2.2 Low-frequency informational efficiency

Hou and Moskowitz (2005) introduce price delays—a low-frequency measure of relative efficiency that relies on the speed of adjustment to market-wide information.⁵ We replicate their annual delay measure and, additionally, create an analogous monthly measure. For the annual measure, we follow their approach and compute weekly Wednesday-to-Wednesday returns for each stock. We regress these returns on contemporaneous and four weeks of lagged market returns over one calendar year. Specifically, we run the following regression:

$$r_{j,t} = \alpha_j + \beta_j R_{m,t} + \sum_{n=1}^4 \delta_j^n R_{m,t,n} + \varepsilon_{j,t}, \quad (1)$$

⁴ Boehmer, Saar, and Yu (2005) apply Hasbrouck's (1993) method to study the effect of the increased pretrade transparency associated with the introduction of OpenBook on the NYSE on stock price efficiency. Boehmer and Kelley (2009) find that institutions contribute to price efficiency using similar approaches. Hotchkiss and Ronen (2002) examine the informational efficiency of corporate bond prices using a simplified procedure suggested by Hasbrouck (1993).

⁵ See, for example, Griffin, Kelly, and Nardari (2010) and Saffi and Sigurdsson (2011) for applications in an international context.

where $r_{j,t}$ is the return on stock j and $R_{m,t}$ is the value-weighted market return in week t . Then, we estimate a second regression that restricts the coefficients on lagged market returns to zero. The delay measure is calculated as $1 - [(R^2(\text{restricted model})/R^2(\text{unrestricted model}))]$.⁶ Similar to an F-test, this measure captures the portion of individual stock return variation that is explained by lagged market returns. A larger delay means a less efficient stock price, in the sense that it takes longer for the stock to incorporate market-wide information.

Relative to the high-frequency efficiency measures, a stock's price delay describes the price discovery process over a much longer horizon. Instead of transaction-to-transaction return dynamics, the delay measure assesses week-to-week return patterns. Yet, the (untabulated) correlation between annual price delays and the annual averages of daily efficiency measures ranges from 0.2 to 0.3, suggesting that these measures mostly capture different aspects of efficiency but also have a common component.⁷

Our analysis covers three years of data, so using an annual variable limits the precision with which we can estimate relations between short selling and price delays. To construct a more powerful test, we modify Hou and Moskowitz's approach and compute monthly price delays using daily, rather than weekly, observations and five days of lagged market returns in regression (1). We require a minimum of fifteen observations per firm per month to compute a monthly price delay. We obtain qualitatively and statistically similar results using annual and monthly delays and report only the latter because of our short sample period.

Finally, we exploit the potential asymmetry in price adjustment speed. Because short sellers primarily benefit from price declines, we expect that information gets incorporated faster with more shorting when market-wide information is negative. We modify the above unrestricted models to isolate negative market returns:

$$r_{j,t} = \alpha_j + \beta_j R_{m,t}^- + \sum_{n=1}^5 \delta_j^{-n} R_{m,t-n}^- + \varepsilon_{j,t}, \quad (2)$$

where $R_{m,t}^-$ equals the daily market return when it is negative. We then use the R^2 from the modified unrestricted model in the denominator to calculate a modified delay measure that captures price adjustment to negative information.

2.3 Post-earnings-announcement drift

Post-earnings-announcement drift is a well-established financial phenomenon that indicates some degree of informational inefficiency in the capital markets.

⁶ To reduce noise in this measure, we require a stock to have at least twenty weekly returns during a calendar year.

⁷ Another low-frequency relative efficiency measure is the R^2 from a market model regression as suggested in Morck, Yeung, and Yu (2000). They argue that lower R^2 indicates more firm-specific information and can thus be used as a measure of information efficiency of stock prices. However, recent work casts doubt on this interpretation and suggests that R^2 does not capture information well (Griffin, Kelly, and Nardari 2010; Saffi and Sigurdsson 2011).

Ball and Brown (1968) first document that abnormal returns of stocks with positive earnings surprises tend to remain positive for several weeks following the earnings announcement and remain negative for stocks with negative surprises. This return pattern generates an arbitrage opportunity for savvy traders. If short sellers are sophisticated traders who attempt to exploit this opportunity, we expect shorting to increase immediately following negative earnings surprises. If short sellers make prices more informationally efficient, the increased shorting activity following negative surprises should attenuate the post-earnings-announcement drift. We use this event-based test to supplement our previous two measures of informational efficiency.

Battalio and Mendenhall (2005) and Livnat and Mendenhall (2006) show that earnings surprise measures based on analyst forecasts are easier to interpret than those obtained from a time-series model of (Compustat) earnings, because the former are not subject to issues, such as earnings restatement and special items. We compute earnings surprises as the difference between actual earnings and the most recent monthly I/B/E/S consensus forecasts, scaled by the stock price two days before the announcement date. We construct abnormal returns as a stock's raw returns net of value-weighted market returns and measure the drift as the cumulative abnormal return following each earnings surprise.

2.4 Return reversals at the daily frequency

Opponents of unrestricted short selling often allege that short selling puts excess downward pressure on prices.⁸ As a result, these opponents claim, prices are too low relative to fundamental values when short sellers are active. A related allegation is that short sellers can manipulate prices by shorting intensely, thereby driving prices down below their efficient values. Once these stocks are undervalued, the short sellers could then cover their positions as the true valuations are slowly revealed and prices reverse toward their efficient values. Both of these scenarios imply that short sellers are more active on days when prices decline and especially so when these declines are not related to fundamental information. We provide evidence on this issue by selecting large price moves and looking at short sellers' behavior around these extreme return days.

3. Shorting Flow and the Short-horizon Efficiency of Transaction Prices

Relative short-horizon efficiency describes how closely transaction prices follow a random walk, and we estimate how short-selling flow affects the degree of short-term efficiency. We regress daily measures of efficiency on lagged shorting and control variables. As the relevant measures of efficiency and shorting are available at the daily frequency, these tests are quite powerful.

⁸ For public concerns or issuers' comments, see SEC Release No. 34-58592 or the NYSE survey on short selling ("Short selling study: The views of corporate issuers," October 17, 2008).

We use the following basic model to test hypotheses about the effect of short selling on efficiency:

$$\text{Efficiency}_{i,t} = \alpha_t + \beta_t \text{Shorting}_{i,t-1} + \gamma_t \text{Controls}_{i,t-1} + \varepsilon_{i,t}. \quad (3)$$

The dependent variable is either the pricing error, $\sigma(s)/\sigma(p)$, or the absolute value of midquote return autocorrelation, $|\text{AR30}|$. Following Boehmer, Jones, and Zhang (2008), we standardize daily shorting flow by the stock's daily share trading volume. This standardization makes shorting activity comparable across stocks with different trading volumes. If more shorting systematically contributes to greater price efficiency, stock prices should deviate less from a random walk, implying a negative β . We lag all explanatory variables by one period to mitigate possible effects of changes in price efficiency on these contemporaneous explanatory variables.⁹

Extant research suggests several control variables that are potentially associated with price efficiency. We include measures of execution costs, order imbalances, share price, market capitalization, and trading volume as controls in our base regressions. To measure execution costs, we use relative effective spreads (measured as twice the distance between the execution price and the prevailing quote midpoint scaled by the prevailing quote midpoint).¹⁰ Higher execution costs make arbitrage less profitable and therefore deter the entrance of sophisticated traders, whose trading helps keep prices in line with their fundamentals. This reasoning suggests that stocks with higher trading costs tend to deviate more from their fundamental values and thus are less efficiently priced. Another variable that may be closely related to price (in)efficiency is one-sided trading pressure. If excess demand is not immediately absorbed by liquidity providers on the other side of the imbalance, less efficient prices will result, at least temporarily. If short selling is related to the degree of one-sided trading pressure in either direction, our results may not reflect the effect of shorting but rather the liquidity needs of other traders. We control for this possibility by including the absolute value of order imbalances in the regressions. We use Lee and Ready's (1991) algorithm to classify trades into buy-signed trades, where buyers are more aggressive than sellers, and sell-signed trades, where sellers are more aggressive than buyers. We compute daily order imbalance for each stock as the difference between buy-signed and sell-signed volume scaled by total trading volume.

We include the volume-weighted average price (VWAP) to control for differences in price discreteness that can potentially affect efficiency.¹¹ Larger

⁹ The lagged explanatory variables can be interpreted as instruments for their contemporaneous values. Results using contemporaneous values are qualitatively the same.

¹⁰ Controlling for relative effective spreads serves another purpose in the pricing error regression. The pricing error reflects the information-uncorrelated (i.e., temporary) portion of total price variance. Because the effective spread measures the total price impact of a trade and thus could conceivably be related to the pricing error, controlling for it can help isolate changes in efficiency from changes in liquidity.

¹¹ Using closing prices produces qualitatively identical results.

and more actively traded stocks may be easier to value. Moreover, Chordia and Swaminathan (2000) show that, after controlling for size, high-volume stocks tend to respond more quickly to information in market returns than do low-volume stocks. Thus, we include both variables in our models. As the natural logs of trading volume and market capitalization are highly correlated (the correlation coefficient is 0.75), we orthogonalize volume with respect to size. Specifically, throughout the article, we use residuals from regressing log volume on log of market capitalization. Results remain qualitatively similar without this orthogonalization. We include the lagged dependent variable to control for potential persistence in relative price efficiency.¹²

Recent literature suggests two additional important variables that should be considered in studying price efficiency. First, because analyst coverage can improve a firm's informational environment, we control for the number of sell-side analysts lagged by one month (Brennan and Subrahmanyam 1995). We obtain the monthly number of analysts producing annual forecasts from I/B/E/S. Second, Boehmer and Kelley (2009) find that institutional investors contribute to greater informational efficiency. We control for institutional holdings so we can focus on the marginal effect of shorting over and above the effect of institutional holdings. As in Boehmer and Kelley (2009), we use lagged quarterly holdings from the 13F filings in the CDA Spectrum database standardized by the number of a firm's shares outstanding.

3.1 Descriptive statistics

Panel A in Table 1 presents time-series means of cross-sectional summary statistics for the main variables in our analysis. Relative shorting volume accounts for close to 20% of total trading volume during the sample period. A 10% standard deviation reveals a large variation in shorting activity across stocks. Price efficiency measures also exhibit substantial cross-sectional variation. Because firm size, trading volume, share price, and number of analysts are skewed, we use their natural logarithms in our estimation.

Panel B in Table 1 reports time-series averages of monthly cross-sectional correlations between shorting and price efficiency. The three measures of informational efficiency are positively correlated. Correlations range from 0.07 (between delay and $|AR30|$) to 0.23 (between delay and pricing error). This suggests that these three measures have a common component but mostly capture different aspects of price efficiency. It is notable that each of the three price efficiency measures is negatively related to shorting, which provides initial evidence that short selling is associated with greater relative price efficiency. Of course, these correlations are only suggestive, and we conduct more rigorous tests to formalize this observation.

¹² Whereas price volatility is conceivably related to short-term efficiency, both of our dependent variables are already scaled by a volatility measure. Therefore, we do not add volatility as an explanatory variable to the model.

Table 1
Summary statistics

Panel A: Descriptive statistics

Variable	Mean	Median	SD
$\sigma(s)/\sigma(p)$	0.095	0.062	0.104
AR30	0.248	0.218	0.177
Shorting (%)	19.7	18.4	9.9
Volume (Thousands)	1,530.893	542.210	3,639.900
RES	0.0011	0.0007	0.0012
VWAP (\$)	36.39	31.91	25.25
Price (\$)	36.42	31.90	25.31
OIB	0.154	0.118	0.146
Size (\$Billions)	8.808	2.185	25.479
InstOwn (%)	69.9	75.1	21.5
NumAnalyst	10	8	6

Panel B: Average monthly correlation between shorting and efficiency

	$\sigma(s)/\sigma(p)$	AR30	Price delay
$\sigma(s)/\sigma(p)$	1.00		
AR30	0.15	1.00	
Price delay	0.23	0.07	1.00
Shorting	-0.16	-0.06	-0.14

The sample includes a daily average of 1,361 NYSE-listed common stocks from January 2005 to December 2007. Panel A reports time-series means of daily cross-sectional summary statistics. $\sigma(s)$ is the standard deviation of the discrepancies between log transaction price and the efficient price based on Hasbrouck (1993). $\sigma(p)$ is the standard deviation of intraday transaction prices. |AR30| is the absolute value of the thirty-minute quote midpoint return autocorrelation. Shorting is calculated as shares shorted standardized by trading volume on a given stock day. Volume is daily share trading volume. RES is daily volume-weighted relative effective spreads. VWAP is daily volume-weighted average price. Price is a stock's daily closing price. |OIB| is the absolute value of daily share order imbalance standardized by share volume, where order imbalance is the difference between buyer-initiated trades and seller-initiated trades based on Lee and Ready's (1991) algorithm. Size is daily market value of equity measured as price times shares outstanding. InstOwn is the fraction of shares outstanding owned by institutions at the end of each quarter. NumAnalyst is monthly number of sell-side analysts producing annual forecast of firm earnings. Panel B reports the time-series averages of monthly cross-sectional correlations between shorting and three efficiency measures, $\sigma(s)/\sigma(p)$, |AR30|, and monthly price delay estimated analogously to the annual price delay in Hou and Moskowitz (2005).

3.2 Basic result

We employ a standard Fama and MacBeth (1973) two-step procedure to estimate Model 3. In the first stage, we run daily cross-sectional regressions of price efficiency on lagged shorting activity and controls. In the second stage, we draw inferences from the time-series average of these regression coefficients. This method picks up the cross-sectional effect of shorting on price efficiency and is less susceptible to cross-sectional correlations among regression errors than a pooled cross-sectional time-series regression. To correct for potential autocorrelation in the estimated coefficients, we report Newey-West standard errors with five lags.¹³

Table 2 contains the regression results. Models 1 and 2 use pricing errors as the efficiency measure, whereas Models 3 and 4 use $\ln|AR30|$. For each measure, we present the base model and a model augmented by the number of analysts and institutional holdings. Lagged daily shorting flow has a

¹³ Results are not sensitive to other reasonable lag lengths for Newey-West standard errors.

Table 2
Fama-MacBeth regressions of high-frequency price efficiency on shorting flow

	$\sigma(s)/\sigma(p)$ Model 1		$\sigma(s)/\sigma(p)$ Model 2		Ln AR30 Model 3		Ln AR30 Model 4	
	Coef	<i>p</i> -Values	Coef	<i>p</i> -Values	Coef	<i>p</i> -Values	Coef	<i>p</i> -Values
Intercept	0.250	0.00	0.241	0.00	-1.613	0.00	-1.599	0.00
LagShorting	-0.066	0.00	-0.049	0.00	-0.072	0.00	-0.093	0.00
LagLnVWAP	-0.013	0.00	-0.012	0.00	-0.011	0.00	-0.010	0.01
LagLnsize	-0.011	0.00	-0.009	0.00	-0.008	0.00	-0.004	0.02
LagLnVolume	-0.019	0.00	-0.015	0.00	-0.011	0.00	-0.012	0.00
LagRES	16.571	0.00	17.439	0.00	-3.281	0.00	-2.634	0.09
Lag OIB	0.048	0.00	0.039	0.00	0.003	0.78	0.019	0.10
LagDV	0.432	0.00	0.393	0.00	0.004	0.00	0.004	0.00
LagInstOwn			-0.022	0.00			-0.003	0.73
LagLnNumAnalyst*100			-0.002	0.00			-0.010	0.00
Adjusted R^2	0.505		0.474		0.003		0.004	

This table reports daily Fama-MacBeth regression results for NYSE-listed common stocks from January 2005 to December 2007. $\sigma(s)$ is the standard deviation of the discrepancies between log transaction price and the efficient price based on Hasbrouck (1993). $\sigma(p)$ is the standard deviation of intraday transaction prices. |AR30| is the absolute value of the thirty-minute quote midpoint return autocorrelation. Shorting is shares shorted standardized by shares traded on a given stock day. RES is the daily value-weighted relative effective spreads. VWAP is daily volume-weighted average price. Size is the market value of equity. Volume is daily share trading volume orthogonalized with respect to size. |OIB| is the absolute value of daily share order imbalance standardized by share volume, where order imbalance is the difference between buyer-initiated trades and seller-initiated trades based on Lee and Ready's (1991) algorithm. DV is the dependent variable. InstOwn is the fraction of shares outstanding owned by institutions. NumAnalyst*100 is the number of sell-side analysts producing annual forecast of firm earnings (scaled up by 100). Lag refers to the first-order lagged value. Daily variables are lagged one day, InstOwn is lagged one quarter, and NumAnalyst is lagged one month. Ln refers to the natural logarithm. The *p*-values are based on Newey-West standard errors.

significant and negative coefficient in each of these specifications. Controlling for other potential determinants of efficiency, greater shorting flow is associated with smaller pricing errors and smaller autocorrelation and thus faster price discovery. In other words, short selling is associated with prices that deviate less from a random walk and hence are more informationally efficient.¹⁴

The coefficients of most control variables exhibit the expected signs. Larger relative effective spreads (RES) and larger absolute order imbalances (|OIB|) are associated with larger pricing errors. This makes sense because higher transaction costs prevent arbitrageurs from trading on some price deviations and therefore lead to lower efficiency. Greater |OIB| implies larger one-sided trading pressure, which is also associated with lower efficiency. Larger and more actively traded stocks are associated with smaller pricing errors. Consistent with prior literature, greater analyst coverage and more institutional holdings promote efficiency (Boehmer and Kelley 2009). For |AR30|, some control variables (RES and |OIB|) have different signs or are not significant, but the

¹⁴ The dependent variable in Models 1 and 2 in Table 2 is the ratio $\sigma(s)/\sigma(p)$. Thus, the efficiency-enhancing effect of short selling could conceivably arise only because shorting inflates $\sigma(p)$, the standard deviation of share prices over time. We can dismiss this possibility empirically. In unreported regressions similar to Model 2, but with $\sigma(s)$ as the dependent variable, we find that the coefficient on lag shorting is significantly negative even when we control for $\sigma(p)$. Thus, an increase in shorting appears to reduce the pricing error per se, rather than inflate total variance.

main result is qualitatively the same: more short selling appears to reduce midquote autocorrelation and therefore improves efficiency.

3.3 Economic magnitude of shorting's effect on price efficiency

We adopt three complementary strategies for gauging the economic magnitude of short selling—induced changes in efficiency. First, we express the effect of short selling in terms of efficiency standard deviations. Second, we compare the impact of short selling to that of analyst coverage and institutional holdings, which are known determinants of efficiency (see Boehmer and Kelley 2009). Third, we estimate how short selling relates to the half-life of a stock's pricing error.

For the baseline Model 1 in Table 2, the coefficient of shorting is -0.066 . If shorting increases by one standard deviation (0.099 in Table 1), this coefficient implies that efficiency improves by $0.066 \times 0.099 = 0.0065$, which amounts to roughly 10% of the mean pricing error (0.095 in Table 1). Alternatively, moving from a stock where shorting is not possible to a stock with median shorting (0.184 in Table 1), the Hasbrouck pricing error declines by $0.066 \times 0.184 = 0.012$, or by roughly 20% of the median pricing error (0.062 in Table 1). These illustrations suggest that the magnitude of short sellers' impact on price efficiency is economically meaningful. Moreover, these estimates suggest dramatic aggregate effects when broad events, such as shorting bans, affect the ability to short in several stocks contemporaneously.

A second way to put the impact of shorting into perspective is to compare the relative influence of institutional holdings, analyst coverage, and short selling. Specifically, in Model 2, a one-standard-deviation (0.0992) increase in short selling is associated with a $0.049 \times 0.0992 = 0.0049$ decline in pricing errors. A one-standard-deviation increase in LnNumEst100 (0.6945) and InstOwn (0.2146) is associated with pricing error reductions of $0.002 \times 0.6945 = 0.0014$ and $0.022 \times 0.2146 = 0.0047$, respectively. Based on this comparison, variation in short selling has a similar economic effect on efficiency as variation in institutional holdings. At the same time, both shorting and institutional holdings are three times as influential for price efficiency as is analyst coverage.

Third, we examine the association between shorting activity and the half-life of a stock's pricing errors. The half-life represents the time it takes to reduce pricing errors by half, and it is thus one possible measure of how quickly prices incorporate information. Analogous to Hansch (2004), we estimate the following daily stock-level regression:

$$\Delta \text{Efficiency}_d = \alpha + \beta d + \rho \text{Efficiency}_{d-1} + \sum_{i=1}^2 \delta \Delta \text{Efficiency}_{d-i} + \varepsilon_d, \quad (4)$$

where efficiency_d denotes the pricing error on day d . In this specification, the coefficient ρ captures mean reversion in efficiency, and the estimated half-life of pricing errors is $-\ln 2 / \rho$. We estimate Model 4 and compute the half-life for each

stock in our sample (not tabulated). We then regress $\ln(\text{half-life})$ on lag shorting and the same controls as in Table 2. To ease interpretation, all explanatory variables are transformed into decile ranks and then scaled to have a value ranging from zero to one. The coefficient on shorting is roughly $-0.2(t = 5.37)$, implying that the half-life of the pricing error decreases by $e^{-0.2} = 0.8$ days when moving a stock from the lowest to the highest shorting decile when controlling for other potential determinants of price discovery. For comparison, the half-life of stocks in the lowest shorting decile is 1.6 days. Against this benchmark, facilitating short selling doubles the speed at which information is incorporated into prices. We obtain qualitatively identical results when we use continuous explanatory variables.

Overall, these comparisons illustrate that short selling is an important economic driver of price discovery. In the next sections, we show that this basic result is robust to different measures of price discovery, and in Section 7 we show that these results are not likely to be driven by reverse causality.

4. Short-selling Flow and Price Delays

Chordia, Roll, and Subrahmanyam (2005) point out that price discovery occurs mainly within a trading day, and Boehmer and Kelley (2009) find evidence in this direction. However, if prices diverge from fundamentals for periods longer than one day (Dechow et al. 2001), such intraday analysis could erroneously interpret “riding the bubble” behavior as short-term reversion to fundamentals. For this reason alone, it is important to assess the effect of short selling on informational efficiency over longer horizons. In this section, we examine how shorting affects price delays, an efficiency measure estimated at monthly and annual horizons. Price delays reflect the sensitivity of a firm’s returns to contemporaneous and lagged market returns and measure how quickly market-wide information is incorporated into stock prices (Hou and Moskowitz 2005).

To make the results comparable to those in the main tests in Table 2, we include similar control variables. The main difference is that a daily panel underlies Table 2, whereas a monthly panel underlies the price delay tests in this section. In Table 3, we present monthly Fama-MacBeth regressions with Newey-West standard errors (Model 1) and a two-way fixed effect model (Model 2). In untabulated tests, we obtain qualitatively identical results using an annual panel as originally suggested in Hou and Moskowitz (2005).¹⁵

We report two different analyses in Table 3—the effect of monthly delays in general (Panel A) and the effect of only negative information (Panel B). Short selling significantly attenuates price delays in both panels, for both the Fama-MacBeth and the fixed-effects models. This suggests that stocks with

¹⁵ Pooled regressions with month clusters produce similar results.

Table 3
Monthly regression of price delays on shorting

	Model 1 Fama-MacBeth		Model 2 Fixed effects	
	Coef	<i>p</i> -Values	Coef	<i>p</i> -Values
Panel A: Delays				
LagShorting	-0.365	0.00	-0.160	0.00
LagLnVWAP	-0.019	0.00	-0.028	0.01
LagLnsize	-0.020	0.00	-0.057	0.00
LagLnVolume	-0.004	0.57	-0.024	0.00
LagRES	12.794	0.00	2.601	0.24
Lag OIB	0.211	0.00	0.034	0.20
LagDV	0.165	0.00	0.017	0.00
LagInstOwn	0.001	0.94	-0.031	0.15
LagLnNumAnalyst*100	0.027	0.00	-0.021	0.00
Adjusted R^2	0.107		0.280	
Panel B: Price adjustment efficiency to negative news				
LagShorting	-0.528	0.00	-0.189	0.00
LagLnVWAP	-0.027	0.00	-0.022	0.15
LagLnsize	-0.028	0.00	-0.061	0.00
LagLnVolume	-0.005	0.62	-0.029	0.00
LagRES	14.175	0.01	3.076	0.37
Lag OIB	0.282	0.00	0.048	0.25
LagDV	0.125	0.00	-0.010	0.05
LagInstOwn	0.000	0.99	-0.045	0.19
LagLnNumAnalyst*100	0.039	0.00	-0.028	0.00
Adjusted R^2	0.078		0.215	

This table reports results for monthly Fama-MacBeth regressions with *p*-value based on Newey-West standard errors (Model 1) and a firm and month fixed effects panel estimation (Model 2) for NYSE-listed common stocks from January 2005 to December 2007. The dependent variable in Panel A is the monthly price delay, estimated analogously to the annual delay in Hou and Moskowitz (2005). The dependent variable in Panel B is a modified price delay that uses only down market returns in the restricted model. Shorting is the monthly average of daily shares shorted standardized by shares traded. RES is the monthly average of daily value-weighted relative effective spreads. |OIB| is the monthly average of daily absolute value of share order imbalance standardized by share volume. VWAP is the monthly average of daily volume-weighted average price. Size is the monthly average of a firm's daily market value of equity. Volume is monthly share trading volume orthogonalized with respect to size. DV is the dependent variable. InstOwn is the fraction of shares outstanding owned by institutions in the most recent quarter. NumAnalyst*100 is the number of sell-side analysts producing monthly forecasts of firm earnings (scaled up by 100). Ln refers to the natural logarithm. Lag refers to the first-order lagged value. InstOwn is lagged one quarter, and all other variables are lagged one month. Regression intercepts are included but not tabulated.

more shorting activity incorporate public information significantly faster into prices than those with less shorting. As expected, the effect is between 18% and 45% stronger for negative information, depending on whether we use Fama-MacBeth or the fixed-effects panel for estimation.

To better understand the economic significance of these effects, we look at their absolute magnitude by itself and also compare it to the impact that institutional holdings and analyst coverage have on delays. Based on Model 1 in Panel A, we calculate that a one-standard-deviation increase in shorting (0.068 at monthly frequency) reduces delay by $0.365 \times 0.068 = 0.092$. This reduction corresponds to 21% of the median delay (0.437), or 0.34 of its standard deviation (0.272). This suggests that the economic importance is greater using the delay

measure than for the intraday analysis. Moreover, neither analyst coverage nor institutional holdings improve efficiency in this model. In fact, institutional ownership is not significant in any of the four models in Table 3, and analyst coverage is associated with better efficiency only in the fixed effects models. Taken together, these observations indicate that shorting's impact on efficiency is economically meaningful, and it clearly dominates the impact of institutional holdings and, to a large extent, that of analyst coverage.

These findings substantiate the core result that shorting enhances the informational efficiency of prices. Specifically, price delays and our transaction-based approach in Table 2 reflect quite different dimensions of the price discovery process. This suggests that the efficiency improvements that are associated with short selling manifest themselves both in intraday transactions prices and in low-frequency measures of price discovery.

5. Short Selling and Post-earnings-announcement Drift

Returns tend to be positive after positive earnings surprises and negative after negative surprises—in other words, prices seemingly do not fully incorporate earnings-related information at the time of the announcement (see Ball and Brown 1968). Bernard and Thomas (1989, 1990) suggest that such post-earnings-announcement drift (PEAD) is a manifestation of investors' failure to recognize the information in the earnings surprises. Because prices tend to drift upward (downward) following a positive (negative) earnings shock, this predictable pattern creates a potential arbitrage opportunity for savvy traders. We have two hypotheses about short selling in the context of PEAD. First, if short sellers are sophisticated traders who attempt to exploit this opportunity, we expect more shorting immediately following negative earnings surprises. Second, if short sellers enhance efficiency and are successful in aiding the price discovery process, the increased shorting activity after negative surprises should at least attenuate PEAD. To test these hypotheses, we examine the two weeks following the announcement, because this is when we expect active short sellers to have the strongest influence on stock prices. After looking at short-term and long-term measures of informational efficiency, this event-based test is our third main approach to examining the relation between shorting and the price discovery process.

In this section, we report some descriptive statistics for shorting around both positive and negative earnings surprises, but we concentrate our analysis on the response of short sellers to negative surprises. We do this because it is not clear how to interpret changes in short selling after positive surprises. For example, suppose short sellers know the true value of a stock and observe that the market underreacts to the negative information in an earnings announcement. Then, traders would short more intensely to take advantage of this arbitrage opportunity, and our test is designed to detect this change in shorting activity. But, if short sellers observe that the market underreacts to the

positive information in an announcement, they can react in two ways—either by reducing shorting or by increasing purchases. However, more likely than not, traders do not have a short transaction planned for this day, and thus it is more likely that the response will be more intense purchases, rather than less intense shorting. Unfortunately, we cannot observe the long transactions of the short sellers in our sample, which makes the effects of short selling around positive surprises hard to interpret. For this reason, our analysis in this section focuses on negative earnings surprises.

Our sample covers 15,536 earnings announcement events. We use a simple portfolio approach to examine how short sellers respond to earnings surprises. Specifically, each quarter, we sort firms into quartile portfolios, according to the earnings surprise measures, with quartile 1 containing stocks with the most negative surprises and quartile 4 containing those with the most positive surprises. To check whether PEAD is present during our sample period, we compute announcement-related cumulative abnormal returns (CARs), defined as a stock's raw return minus the value-weighted market returns. Table 4 reports equally weighted CARs for each quartile. Consistent with prior findings, the announcement effects are very strong: abnormal returns during the three-day window $(-1, 1)$ centered on the announcement date are large and negative (-3.26%) for portfolios with the most negative surprises and are large and positive (3.40%) for positive surprises. More importantly, we observe significant PEAD for each but the third largest surprise quartile: prices of stocks with good (bad) surprises continue to drift upward (downward) after the announcement. Finally, PEAD is monotonic across quartiles—one-week cumulative abnormal returns starting from the second day after the announcement date $(2, 6)$ increase monotonically from -0.75% for stocks with the most negative surprises to 0.42% for stocks with the most positive surprises.

We now address our hypotheses that (1) short sellers view the drift period as a mispricing episode and trade accordingly and (2) this promotes price discovery. If short sellers understand and seek to exploit the arbitrage opportunity associated with post-earnings-announcement drift, they will short stocks more intensively in quartile 1 right after observing the market reaction to the announcement.

We first look at shorting and returns graphically in Figure 1. Panel A shows CAR and shorting for negative surprises (Q1). We make several interesting observations. First, shorting increases from about 19.8% of volume at $t - 2$ to about 21.5% at $t + 1$ for the most negative surprises (Q1). This pattern is also confirmed in Panel B of Table 4: the change in shorting from $(-6, -2)$ to $(+2, +6)$ around the announcement date is 1.28% for Q1, which is statistically significant at the 1% level. Second, the main adjustment to shorting activity for Q1 occurs on the day after the announcement, so it seems that short sellers indeed react to the information and corresponding market reaction on that day. Both of these observations support our first hypothesis. Finally, daily returns

Table 4
Abnormal returns around earnings announcement dates

Panel A: Cumulative abnormal returns around earnings announcements sorted on earnings surprises

Days relative to earnings announcement	(-1, 1)	(2, 6)	(2, 11)
Earnings surprise			
Q1 (Most negative)	-3.26%	-0.75%	-0.79%
<i>t</i> -Statistic	-28.18	-8.54	-6.46
Q2	-0.75%	-0.20%	-0.27%
<i>t</i> -Statistic	-7.36	-3.24	-3.49
Q3	1.54%	0.01%	-0.07%
<i>t</i> -Statistic	18.01	0.17	-0.84
Q4 (Most positive)	3.40%	0.42%	0.44%
<i>t</i> -Statistic	32.44	5.62	4.57

Panel B: Average shorting around earnings announcements

Days relative to earnings announcement	[-11, -2]	[-6, -2]	[-1, 1]	[2, 6]	[2, 11]	[2, 6] - [-6, -2]	[2, 11] - [-11, -2]
Earnings surprise							
Q1 (Most negative)	20.21%	20.15%	20.52%	21.43%	21.25%	1.28%	1.03%
<i>t</i> -Statistic	20.06%	19.96%	20.04%	20.24%	20.13%	0.28%	0.06%
Q2	19.56%	19.47%	19.55%	19.32%	19.32%	-0.14%	-0.23%
<i>t</i> -Statistic	19.60%	19.51%	19.13%	18.97%	18.92%	-0.54%	-0.67%

This table presents cumulative abnormal returns around quarterly earnings announcements for NYSE-listed common stocks from January 2005 to December 2007. Each quarter, stocks are sorted into quartiles, according to earnings surprises calculated as the difference between actual earnings and the analyst consensus estimate, scaled by the share price two days prior to the announcement. *, **, *** represent significance at the 0.1, 0.05, and 0.01 level, respectively.

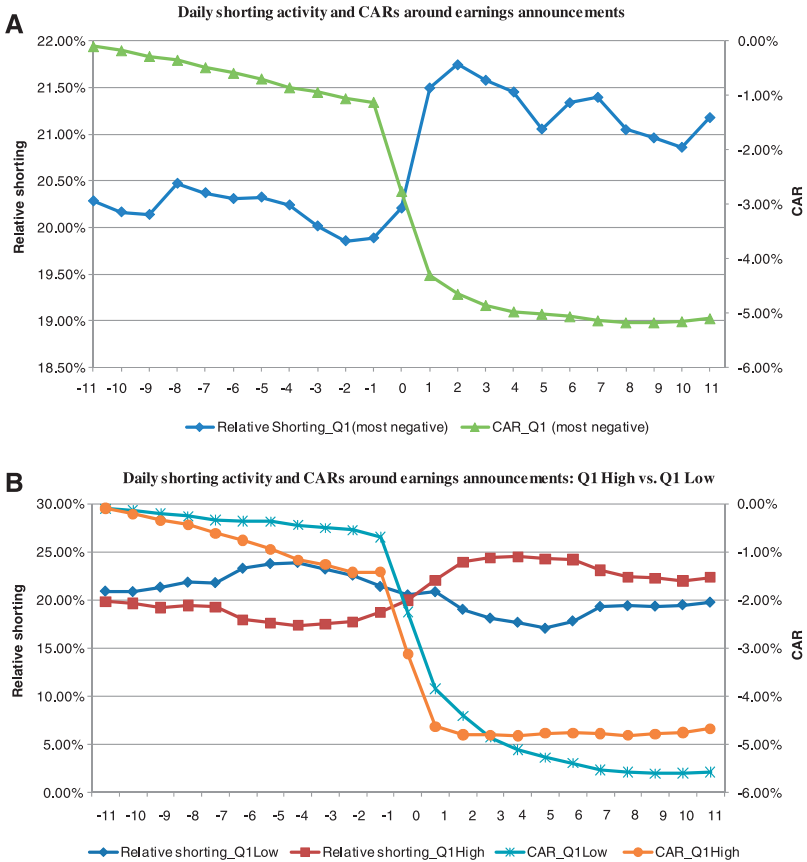


Figure 1
Daily shorting activity and CARs around earnings announcements
 Each quarter between January 2005 and December 2007, stocks are sorted into quartiles (Q1 to Q4) according to earnings surprises calculated as the difference between the actual earnings and analyst consensus estimates, scaled by the share price two days prior to the announcement. Panel A represents the daily shorting and CARs for the most negative quartile (Q1). Panel B splits the Q1 sample based on the change in shorting from the week before the announcement to the week after. High (low) refers to an above- (below-) median change in shorting. CAR is defined as a stock's raw return minus the value-weighted market returns.

move in the direction of the change in shorting: for increases in shorting, we observe a contemporaneous negative return.

In Panel B, we split the Q1 sample based on the change in shorting from the week before the announcement to the week after (more precisely, the change from $(-6, -2)$ to $(+2, +6)$ relative to the announcement date). High-shorting events are Q1 announcements with an above-median change in shorting and conversely for low-shorting events. Both the high-shorting and low-shorting portfolios are associated with large negative returns after

Table 5
Post-earnings announcement drift of portfolios double-sorted on earnings surprises and changes in shorting activity

	Post-earnings announcement drift (2,6)			Post-earnings announcement drift (2,11)		
	Change in shorting		<i>t</i> -Statistic (Low - high)	Change in shorting		<i>t</i> -Statistic (Low - high)
	Low	High		Low	High	
Earnings surprise						
Q1(Most negative)	-1.54% ***	-0.11%	-8.10 ***	-1.77% ***	0.00%	-7.15 ***
<i>t</i> -Statistic	-10.91	-1.00		-9.05	-0.01	
Q2 (Second most negative)	-0.77% ***	0.37% ***	-9.23	-0.89% ***	0.35% ***	-7.97 ***
<i>t</i> -Statistic	-8.20	4.62		-7.87	3.27	

This table reports mean post-earnings announcement drift of firms sorted on earnings surprises and changes in shorting activity around earnings announcements for NYSE-listed common stocks from January 2005 to December 2007. Each quarter, stocks are sorted into quartiles, according to earnings surprises calculated as the difference between the actual number and analyst consensus, scaled by stock prices two days prior to the announcement and then split into two groups based on the median change in average shorting from one week before to one week after the announcement. This table shows only the two most negative surprise quartiles. The drift is calculated as market-adjusted cumulative abnormal returns. *, **, *** represent significance at the 0.1, 0.05, and 0.01 level, respectively.

the announcement, but drift is eliminated only in the high-shorting portfolio. Although we can only speculate why short sellers do not increase shorting in the low-shorting portfolio, the finding that PEAD goes away when short sellers choose to become more active supports our main conclusion so far: short sellers help the price-discovery process and make prices more informationally efficient.¹⁶

The finding that PEAD vanishes after negative earnings surprises with large increases in short selling is consistent with our second hypothesis. We now present a more formal test related to this finding. Each quarter, we sort stocks into quartiles based on earnings surprises. Within each earnings surprise quartile, we again partition stocks into two groups based on changes in shorting activity around the announcement. Table 5 reports one- and two-week post-earnings-announcement drift for this double sort for negative surprises. Again, the evidence suggests that more shorting enhances efficiency, in this case by reducing the drift. Using the one-week drift, stocks with very negative earnings surprises (Q1) and large increases in shorting exhibit no drift—the post-announcement CAR is 11 bp and not statistically different from zero. In contrast, the corresponding low-shorting portfolio experiences a drift of -154 bp. It is not entirely clear to us why short sellers do not arbitrage this 154 bp drift in the same way as they remove the drift in the high-shorting portfolio. But, even with a return this large, it is possible that it is not sufficient to cover round-trip transaction costs, because traders must short into a declining market to take advantage of this temporary mispricing. (Unfortunately, we

¹⁶ The firms in the low-shorting Q1 portfolio are not substantially different from firms in the high-shorting Q1 portfolio along dimensions that are commonly associated with shorting difficulty, such as price level and institutional holdings. Moreover, none of the results in this section are sensitive to the presence of the uptick rule—results are qualitatively identical for pilot and nonpilot stocks.

cannot observe the return that would have accrued to the high-shorting portfolio had the shorting not increased—but it could possibly be even larger.) If expected transaction costs are high, arbitrage is risky ex ante, and this may prevent traders from establishing a large short position designed to take advantage of the drift. Alternatively, PEAD could arise partly because prices are slow to adjust and partly because of other reasons that do not involve mispricing (Sadka 2006). In this case, realized drift would overstate the return arbitrageurs can earn. But, traders in the high-shorting group do bring prices closer to fundamentals, and we obtain almost identical results for a two-week window. Overall, these event-based results provide additional support for the hypothesis that short sellers help make prices more efficient.

Recognizing that other factors influence the magnitude of the PEAD, we use regression analysis to incorporate critical control variables. To estimate the effect of shorting on PEAD that cannot be attributed to those other factors, we estimate the following regression model:

$$\begin{aligned}
 CumMktAdjRet_{i,t} = & \alpha + \beta_1 DUE_{i,t} + \beta_2 DUE_{i,t} * D\Delta S_{i,t} \\
 & + \beta_3 DUE_{i,t} * DInstOwn_{i,t} + \beta_4 DUE_{i,t} * DTO_{i,t} \\
 & + \beta_5 DUE_{i,t} * DSize_{i,t} + \varepsilon_{i,t}.
 \end{aligned} \tag{5}$$

The dependent variable is the cumulative market-adjusted abnormal return from day 2 to day 6. DUE represents the scaled decile ranking of earnings surprises (Bartov, Radhakrishman, and Krinsky 2000). Specifically, each quarter, we sort unexpected earnings into deciles and scale decile ranks to range between zero (most negative earnings surprises) and one (most positive earnings surprises). With nonzero PEAD, we expect a positive coefficient on β_1 . To estimate the marginal effect of shorting on the slope of DUE, we include $DUE * D\Delta SS$, the interaction between DUE and a scaled decile rank variable representing changes in daily average shorting activity from $(-6, -2)$ to $(+2, +6)$ around earnings announcements. Specifically, each quarter, we sort the change in shorting activity in descending order. We form deciles and scale the ranks to range from zero (largest increase in shorting) to one (largest decrease in shorting). If short sellers attempt to exploit PEAD and have an important effect on post-announcement prices, β_2 should be negative: firms with negative earnings surprises and a greater increase in shorting should exhibit smaller drift.

We include additional controls suggested in the literature. Following Bartov, Radhakrishman, and Krinsky (2000), all controls are in the form of decile ranks interacted with DUE. Bartov, Radhakrishman, and Krinsky (2000) and Ke and Ramalingegowda (2005) show that institutional investors are sophisticated investors who exploit earnings patterns, so we include last-quarter institutional holdings scaled by shares outstanding as a control. We also include several variables that proxy for liquidity, which may be associated with earnings drift (Chordia et al. 2009; Sadka 2006). These liquidity proxies

Table 6
Regression analysis of the impact of short selling on PEAD

	Model 1		Model 2		Model 3		Model 4	
	Coef	<i>p</i> -Value	Coef	<i>p</i> -Value	Coef	<i>p</i> -Value	Coef	<i>p</i> -Value
Intercept	-0.0084	0.00	-0.0080	0.00	-0.0080	0.00	-0.0080	0.00
DUE	0.0295	0.00	0.0299	0.00	0.0318	0.00	0.0323	0.00
DUE*D Δ SS	-0.0291	0.00	-0.0302	0.00	-0.0304	0.00	-0.0304	0.00
DUE*DInstOwn			0.0002	0.93	0.0030	0.17	0.0029	0.18
DUE*DTO					-0.0066	0.00	-0.0065	0.00
DUE*Dsize							-0.0013	0.52
Adjusted R^2	0.0244		0.0265		0.0271		0.0271	

This table shows regressions of the post-earnings announcement drift for NYSE-listed common stocks from January 2005 to December 2007. The dependent variable is the market-adjusted cumulative abnormal returns from day 2 to day 6 following the earnings announcement date. Each quarter, UE, InstOwn, TO, and Size are sorted in an ascending order into deciles, and Δ SS is sorted in a descending order into deciles. For each variable, the "D" prefix indicates the respective decile ranks that are scaled to range between zero and one. UE is calculated as the difference between actual earnings and the analyst consensus estimate, scaled by the share price two days prior to the announcement. Δ SS is the change in short selling from (-6, -2) to (+2, +6) around the announcement date. InstOwn is the institutional ownership as a fraction of shares outstanding in the most recent quarter. TO is the average daily turnover one week before the announcement. Size is the market cap in the most recent quarter.

include dummy variables of the average daily turnover one week prior to the announcement (DTO) and firm size in last quarter (DSize).¹⁷

Table 6 reports the regression results. Consistent with our expectations, the coefficient on DUE is significantly positive, suggesting that negative earnings surprises are followed by downward drift. Institutional ownership is not significant, possibly because of a relatively short sample period with low-frequency data. Turnover, as a proxy for liquidity, significantly reduces drift, consistent with Chordia et al. (2009) and Sadka (2006). Our key variable, DUE*D Δ SS, is significantly negative across all model specifications. So, PEAD is significantly smaller when short sellers act on arbitrage opportunities associated with PEAD, beyond the effect that cross-sectional differences in liquidity have. In the process of arbitraging PEAD, short-selling activity improves the informational efficiency of prices.

6. Short Selling and Extreme Price Movements

Short sellers tend to be contrarians who sell more after periods of positive returns. At an annual frequency, Dechow et al. (2001) show that changes in short interest are positively related to changes in prices. They suggest that short sellers take positions in stocks that experience price run-ups and then cover as prices decline. Diether, Lee, and Werner (2008) show that short sellers are also contrarians at a daily horizon. But, two recent studies provide evidence that, in certain situations, some short sellers destabilize prices by driving prices away from efficient values. Shkilko, Van Ness, and Van Ness (2012) find that some

¹⁷ We also use quartile ranks instead of decile ranks and above-below-median dummies in shorting change. This leaves the results qualitatively unaltered and largely reproduces the results from our double sorts.

short sellers drive down prices too far during extreme price declines. Similarly, Henry and Koski (2010) argue that short sellers are able to push prices too far down just before seasoned equity offerings. Although the objective of our article is to assess the average effect of short sellers as a group, it is useful to extend our analysis in this direction.

More specifically, we look at short selling around extreme price moves and those price moves that are quickly reversed. By definition, price changes that reverse quickly involve no new information—otherwise the price change should be permanent. Such no-information price reversals could arise, for example, when index funds experience outflows and thus become obliged to sell a large quantity of shares. This would temporarily lower prices, inducing other traders to buy these shares. Once the selling pressure subsides, in the absence of stock-specific negative information, prices would then return to the level prior to the large sell. If short sellers are smart traders who understand that the initial negative return is transient, we expect them to reduce their shorting while prices are (temporarily) below their efficient values.

Analysis of these no-information events can shed light on two central issues in the short-selling debate: whether short sellers *cause* the no-information price declines and how short sellers *react* to no-information price declines. Regarding the first issue, the SEC is expressly concerned that short selling may cause “sudden and excessive fluctuations of the prices.”¹⁸ If nefarious short sellers destabilize prices, we expect more intense shorting on extreme down days, especially when the downward price change is unrelated to fundamental information. Conversely, if short sellers help keep prices in line and close to their efficient values, we expect them to short less on extreme down days, especially when the initial price shock is unrelated to fundamental information. Subsequent to extreme returns, we could expect nefarious traders to increase shorting after observing large downward price changes in the hope of covering at still lower prices. In contrast, efficiency-enhancing short sellers would reduce sales after observing no-information price declines (and perhaps purchase shares, but we do not observe this in our data).

To identify extreme return days for each stock, we make subjective decisions regarding the length of return windows, the nature of price reversals, and the definition of “extreme” returns. We select days with returns exceeding two standard deviations measured over the past twenty trading days. We classify these events into one of four categories, depending on what happens on the next day: a continuation, a small reversal, a large reversal, or an overshooting reversal. If we have a large negative return on day t , a continuation is any nonpositive return on day $t + 1$. A reversal of less than 20% of the down day’s return would be classified as a small reversal, and one that reaches more than 20% but remains below the closing price on day $t - 1$ is a large reversal. An

¹⁸ See SEC Release No. 34-58592.

overshooting reversal means that the closing price on day $t+1$ exceeds the closing price on day $t-1$. We proceed analogously for extreme positive returns events, but our main focus in this section is on extreme negative price shocks.

In Figure 2, we graph daily time series of cumulative returns and short selling around extreme return events. The four panels correspond to the type of reversal on day $t+1$. In addition to the graphical discussion, we test whether day 0 returns and the next-day reversal magnitudes are significantly linked to contemporaneous short selling. Specifically, we regress day 0 returns and

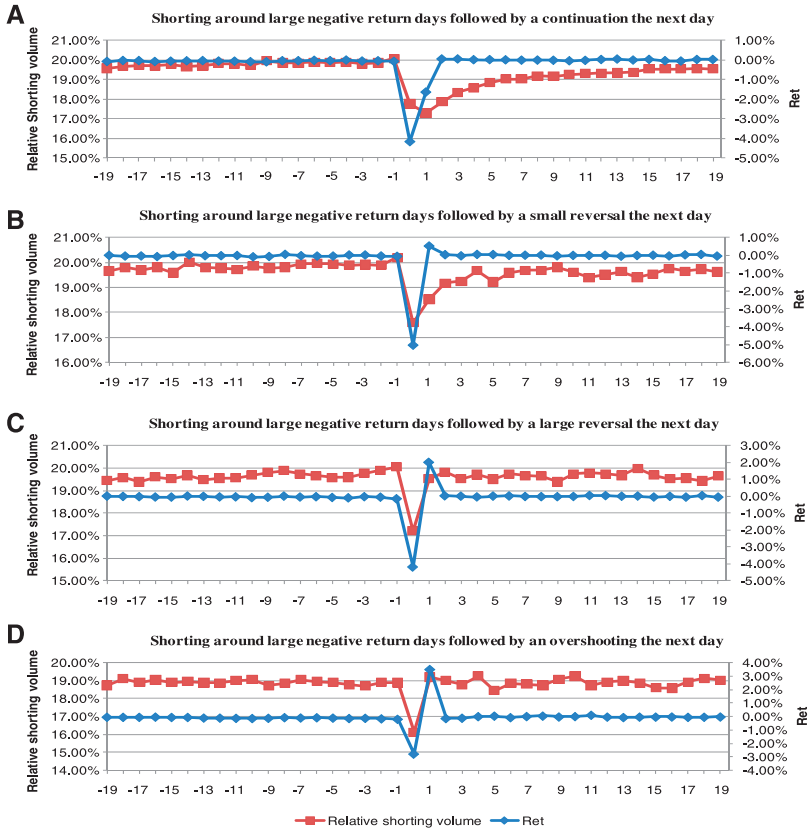


Figure 2
Short selling around large negative return days

Panels A, B, C, and D show relative shorting volume around large negative return days followed by continuation, a small reversal, a large reversal, and an overshooting reversal the next day, respectively. Large negative return days indicate down days when a stock's return is below twice its twenty-day moving standard deviation. Continuation refers to the case in which the next day's return keeps going down (17,113 observations). A small reversal refers to the case in which the next day's return is positive but reverses by less than 20% of the down day's return (3,822). A large reversal refers to the case in which the next day's return reverses by more than 20% but less than 100% of the down day's return (7,815). An overshooting reversal indicates a reversal to a price higher than the one on the day prior to the down day (2,519). Relative shorting volume is shorting volume standardized by trading volume. Return is raw return in excess of CRSP value-weighted return.

Table 7
Short selling around extreme negative returns and their subsequent reversal

Dependent variable	R($t = 0$)		R($t = 1$) / R($t = 0$)	
	Coef	p -Value	Coef	p -Value
Intercept	-0.054	0.00	0.303	0.00
Δ abnShorting	0.003	0.18	0.311	0.00
Δ abnOIB	-0.002	0.02	0.117	0.00
abnTurnover	-0.631	0.00	-1.504	0.00
abnVolatility	-0.555	0.00	6.254	0.00
abnRES	0.256	0.01	-18.372	0.00
lnsize	0.001	0.00	0.000	0.94
LnVWAP	0.004	0.00	0.018	0.04
InstOwn	0.002	0.01	0.030	0.26
LnNumAnalyst*100	0.000	0.118	-0.003	0.75
Adjusted R^2	0.69		0.04	

This table presents regression analysis of shorting around large negative returns on day $t = 0$ that are followed by a reversal on the next day ($t = 1$). The dependent variable captures the reversal magnitude and is defined as $|R(t = 1)| / |R(t = 0)|$, where R is the excess return over the CRSP value-weighted market return. Shorting is shorting volume scaled by trading volume. Turnover is measured as shares traded divided by shares outstanding. OIB refers to daily relative share order imbalance (the difference between buys and sells standardized by trading volume). Volatility refers to intraday volatility measured as the max. price minus min. price and then scaled by VWAP. RES is trade-weighted relative effective spread. Shorting, OIB, Turnover, Volatility, and RES are expressed as abnormal measures, defined as the difference between the day t value and the corresponding past twenty-day moving average. Size is the market capitalization two days before the reversal event. VWAP is the volume-weighted average price two days before the reversal event. InstOwn refers to institutional ownership relative to total shares outstanding in the most recent quarter before the event. NumAnalyst*100 is the number of sell-side analysts producing annual forecast of firm earnings (scaled up by 100) in the most recent month before the event. Δ indicates changes between day 1 and day 0. Ln refers to the natural logarithm.

reversal magnitudes (measured as the absolute value of day 1 returns divided by day 0 returns) on abnormal short selling and the same controls as in Table 2. Abnormal short selling is defined as the change in shorting on day 0 or day 1 relative to the preceding twenty-day historical average (using, as before, shares shorted normalized by trading volume). If extreme returns are indeed information free and short sellers' trading pushes prices toward their efficient values, we expect that shorting should decrease on day 0 and increase on day 1, and it should increase more when the next-day reversal is larger. Thus, the coefficients on abnormal shorting should be positive in both regression models if short sellers improve efficiency around extreme return events. Table 7 contains the estimated coefficients from these models. We limit our discussion to extreme negative returns but obtain an almost exact mirror image when we repeat the analysis on analogously defined positive return shocks.¹⁹

¹⁹ We present both the graphs and the regressions using daily market-adjusted returns, but the results are qualitatively identical when we use raw returns to identify extreme return events and subsequent price reactions. We obtain qualitatively identical results when we include shorting on day -1 in the first regression. Moreover, all results in this section are robust to reasonable variations of the assumptions: changing the break points for reversal categories (replacing the 20% cutoff with 10% or 30% cutoffs), lengthening the window over which extreme returns are defined (from 10 days to 20, 30, 60, or 90 days), excluding earnings announcement dates from these extreme return events, or examining pilot and control stocks separately all leave the results qualitatively unchanged.

We first examine shorting around the large negative day 0 returns in Figure 2. The price drop averages about 4%–5% across the four panels. By construction, the shock in Panel A experiences a continuation on the next day, and we do not know whether or not the returns are eventually reversed or whether new information is partly responsible for these events. We show the continuation graphs for completeness but focus on Panels B through D, where returns reverse on the next day. Here, we know that the day 0 return shocks are transient and can investigate whether short sellers trade as if they understand that these returns are not information based. If shorters attempted to manipulate prices or exacerbate price declines for these reversals, we would expect shorting to increase, either on the down day or before. None of the graphs supports this conjecture: shorting is fairly flat before the drop in all cases and then *declines* dramatically on the day of the price decline. Controlling for several relevant variables, the shorting coefficient in the first regression in Table 7 is not significantly different from zero. Taken together, these results suggest that short sellers, as a group, do not worsen the price decline on day 0. If anything, they reduce their activity as suggested by Figure 2.

Next, we look at the magnitude of day 1 returns relative to the magnitude of the day 0 shock. In Panel A, these returns are negative; in all other panels, they are positive, and by construction these returns increase monotonically from Panel A to Panel D relative to the day 0 price decline. If the extreme price declines on the previous day are temporary and short sellers interpret them correctly, we would expect shorting on day 1 to increase with the magnitude of the reversal. For example, if prices reverse partially (Panel B), informed short sellers may expect further reversal and limit their trading activity. In Panel D, we expect the informed short seller to trade more intensely during and after the overshooting reversals because if there is no new information, prices have increased too much. The day 1 results are consistent with these arguments. In Panel A, price declines continue and shorting remains low. On days with small reversals (Panel B), short selling increases slightly from day t but remains substantially lower than before the shock for the next five trading days. On days with large reversals (Panel C), short sellers resume their pre-event activity level quickly. Finally, for the overshooting returns (Panel D), short sellers increase their shorting activity the most. Notably, day 1 shorting activity is monotonically related to the reversal magnitude: we observe more short selling relative to pre-event means as we move from Panel A to Panel D. The second regression in Table 7 shows that the relation between shorting and reversal magnitude is statistically meaningful. Adding controls, short selling is positively related to the reversal magnitude, and the coefficient is significant at the 1% level. Both the time-series graphs and the regression tests are consistent with the view that short sellers trade to keep prices in line with their efficient values.²⁰

²⁰ Results for the opposite event (extreme positive returns) yield almost exact mirror-image results. We again classify stocks into four categories in accordance with $t+1$ returns. As we would expect for short sellers who

Overall, these results are consistent with Dechow et al.'s (2001) and Diether, Lee, and Werner (2008) findings that short sellers act as contrarians. But, our results are inconsistent with Shkilko, Van Ness, and Van Ness (2012), who argue that short sellers worsen price declines around extreme return days. Contrary to their interpretation of shorting around negative return events, we show that short sellers' trading helps accelerate price discovery during these extreme events. Shorters sell more when prices jump unusually high, they short less when prices drop unusually low, and they swiftly change their behavior as prices reverse—all consistent with efficiency-enhancing trading patterns. Moreover, for extreme returns that are reversed on the next day, short sellers appear to recognize the temporary nature of these price swings. As a result, their trading provides liquidity to the market and keeps prices in line, even during these volatile episodes.

7. Robustness

Our key finding is that daily short-selling activities facilitate price discovery and make prices more informationally efficient. We provide evidence along four dimensions of efficiency by looking at how short selling relates to deviations of transaction prices from a random walk, low-frequency price delays, post-earnings-announcement drift in event time, and non-information-based large price movements. We view the transaction-based analysis as the strongest convincing argument in this set and discuss additional sensitivity tests in this direction.

7.1 The effect of short-selling constraints

When traders face shorting constraints, theory tells us that negative information is not fully incorporated into prices (Miller 1977) or more slowly (Diamond and Verrecchia 1987) than without shorting constraints. This slows price discovery, and we expect the informational efficiency of prices to decline with the stringency of shorting constraints. We conduct a supplemental experiment in this regard and look at the Reg SHO experiment between 2005 and 2007, which exempted one-third of the Russell 3000 stocks (a volume-stratified sample) from the uptick rule. We conduct a difference-in-difference experiment that compares the effect of shorting “pilot” stocks (not subject to the uptick rule) to the effect of shorting the volume-matched set of other stocks in the pre- and post-Reg SHO periods.²¹

view the positive return as transient, the day 0 price increases are associated with a substantial increase in shorting activity in each case. This is consistent with the contrarian nature of short selling (see Diether, Lee, and Werner 2008). Equally important, and similar to Figure 2, we find that shorting on day 1 is monotonically related to the magnitude of return reversals. Shorting is highest when prices continue to increase and lowest when prices fall below their day -1 level.

²¹ The uptick rule, commonly known as the tick test, requires that short selling in exchange-listed stocks occur only at an uptick or a zero-plus tick. That is, short sales in these stocks need to transact above the last trade price or

To implement this test, we augment Model 2 in Table 2 with three additional variables: a “*pilot*” dummy, indicating pilot stocks; a “*post*” dummy, indicating the period over which price tests were removed for pilot stocks; and an interaction $pilot*post*Shorting$. The interaction coefficient represents a difference-in-difference test of the impact of removing the uptick rule on informational efficiency. In this test (not tabulated), the main results from Table 2 still hold. Importantly, the interaction coefficient is -0.005 and significant at the 1% level. Comparing it to the main shorting coefficient in this model, -0.029 , this implies that the efficiency-enhancing effect of short selling becomes $0.005/0.029 = 17\%$ stronger when the uptick rule is removed.

7.2 Distribution of shorting flow

Shorting flow is skewed. To assure that distributional issues do not affect our results, we use decile ranks in place of shorting flow to test for efficiency effects. Specifically, on each day, we sort stocks into deciles based on the prior day’s relative shorting volume. Then, we use the decile ranks in regression model (3). This approach reduces the influence of outliers on the estimates. Our main finding (not tabulated) remains unchanged with this alternative shorting measure: stocks ranked higher in terms of relative shorting flow are associated with significantly smaller values of both pricing errors and return autocorrelations.

7.3 Influence of unobservable firm effects

Our high-frequency results may also be affected by firm-specific effects. To address this possibility, we construct a measure of “abnormal” shorting. Each day, we compare a stock’s relative shorting volume to its own moving average over the past week to determine whether shorting has become more or less intense. This way we identify stocks that experience a shock in their own shorting activity and take into account potential persistence in a firm’s shorting activity. Another way of addressing stock fixed effects is to model them directly in a panel regression. This methodology mitigates the omitted-variable concern with cross-sectional OLS regressions. Both the abnormal-shorting tests and the fixed-effect panel regressions produce qualitatively identical results (not

at the last trade price if the last trade price is higher than the most recent trade at a different price. Because the SEC eliminated the uptick rule for all stocks on July 6, 2007, our sample for this analysis includes pilot stocks and control stocks from January 1, 2005, to July 5, 2007. The SEC selected pilot securities from the Russell 3000 index as of June 25, 2004. First, thirty-two securities in the Russell 3000 index that are neither listed on the American Stock Exchange (AMEX), nor on the New York Stock Exchange (NYSE), nor on NASDAQ national market securities (NNM) are dropped. Securities that went public after April 30, 2004, are also excluded. The remaining securities are then sorted into three groups by marketplace and ranked in each group based on average daily dollar volume over the one year prior to the issuance of the order. From each ranked group, the SEC selected every third stock to be a pilot stock starting from the second stock. The remaining stocks are suggested to be used as the control group, where the price test restriction still applies. Of all pilot stocks, 50%, 2.2%, and 47.8% are from NYSE, AMEX, and NASDAQ NNM, respectively. For more information about Reg SHO, see SEC Release No. 50104/July 28, 2004.

tabulated): stocks with higher abnormal shorting are priced more efficiently as observed by smaller pricing errors and autocorrelations.

We also consider additional controls. We include lagged two-week returns to control for short-term momentum. Again, the inclusion of this variable does not remove the effect of shorting on price efficiency. We use turnover in place of log volume in the regressions. To the extent that turnover serves as a proxy for investor attention (see, e.g., Chordia and Swaminathan 2000), it could be related to price efficiency because high-volume stocks tend to respond more quickly to information in market returns than do low-volume stocks. We find that increased turnover makes prices more efficient, but shorting remains significant as well.²²

7.4 Reverse causality

Reverse causality is an important issue that we have not yet formally addressed. It is important, because a plausible story links efficiency to shorting. Institutional investors may prefer to hold efficiently priced stocks because they are less likely to be mispriced. But, stocks with higher institutional holdings are also easier to short (Nagel 2005), because the supply of lendable shares is greater in these stocks. Therefore, efficiently priced stocks may exhibit more shorting activity. If efficiency and shorting are sufficiently persistent, this reverse-causality story could explain the association between efficiency and shorting flow. Although we use prior-day shorting in our analysis to mitigate this concern, we now address it more rigorously.

In the spirit of Granger causality tests, we regress time-series changes in efficiency on lagged time-series changes in shorting for each stock, using the same set of control variables as in Table 2. In contrast to the cross-sectional regressions reported in Table 2, we now construct first differences in all variables and estimate a time-series regression for each stock. We require a stock to be actively traded for at least forty-five days during the sample period to obtain reliable time-series regression estimates. Table 8 reports the cross-sectional mean coefficients from these time-series models. Panel A shows that greater increases in shorting are strongly associated with a greater next-day improvement in efficiency.

To examine reverse causality, we regress changes in shorting on lagged changes in price efficiency using the same controls. Panel B shows that the average coefficient of the lagged change in price efficiency, measured by either the pricing error or the absolute value of autocorrelations, is not significantly related to changes in shorting at the 5% level. This indicates that changes in shorting are not systematically related to prior changes in price efficiency. It is comforting that the time-series results closely parallel those from the

²² We also use residual turnover by orthogonalizing turnover with respect to other control variables in the regression. Shorting still exhibits a reliably negative coefficient.

Table 8**Granger causality tests of changes in price efficiency and changes in shorting activity**Panel A: Dependent variable is change in price efficiency (Δ Efficiency)

	$\Delta\sigma(s)/\sigma(p)$ Model 1		$\Delta\sigma(s)/\sigma(p)$ Model 2		$\Delta\text{Ln} AR30 $ Model 3		$\Delta\text{Ln} AR30 $ Model 4	
	Coef	p-Value	Coef	p-Value	Coef	p-Value	Coef	p-Value
Intercept	0.0004	0.00	-0.0001	0.69	0.0003	0.23	-0.0002	0.86
Lag Δ Efficiency	-0.472	0.00	-0.473	0.00	-0.497	0.00	-0.496	0.00
Lag Δ Shorting	-0.011	0.00	-0.009	0.00	-0.062	0.00	-0.075	0.00
Lag ΔLnVWAP	0.076	0.22	0.064	0.41	-0.396	0.08	-0.442	0.12
Lag ΔLnSize	0.036	0.35	0.038	0.52	0.908	0.00	1.089	0.02
Lag $\Delta\text{LnVolume}$	-0.004	0.00	-0.003	0.00	-0.002	0.52	0.000	0.91
Lag Δ RES	1.870	0.00	1.174	0.12	-8.842	0.28	-17.461	0.13
Lag $\Delta OIB $	0.004	0.00	0.003	0.00	0.013	0.32	0.013	0.39
Lag $\Delta\text{InstOwn}$			0.010	0.20			0.008	0.88
Lag $\Delta\text{LnNumest*100}$			0.000	0.85			0.009	0.14
Adjusted R^2	0.220		0.221		0.250		0.247	

Panel B: Dependent variable is change in relative shorting (Δ Shorting)

	$\Delta\sigma(s)/\sigma(p)$ Model 1		$\Delta\sigma(s)/\sigma(p)$ Model 2		$\Delta\text{Ln} AR30 $ Model 3		$\Delta\text{Ln} AR30 $ Model 4	
	Coef	p-Value	Coef	p-Value	Coef	p-Value	Coef	p-Value
Intercept	0.0001	0.11	0.0002	0.30	-0.0003	0.00	-0.0001	0.66
Lag Δ Efficiency	-0.002	0.24	-0.004	0.15	-0.0001	0.07	-0.0001	0.14
Lag Δ Shorting	-0.401	0.00	-0.398	0.00	-0.403	0.00	-0.399	0.00
Lag ΔLnVWAP	-0.337	0.00	-0.393	0.00	-0.359	0.00	-0.394	0.00
Lag ΔLnSize	0.255	0.00	0.279	0.00	0.251	0.00	0.273	0.00
Lag $\Delta\text{LnVolume}$	0.002	0.00	0.002	0.00	0.003	0.00	0.002	0.00
Lag Δ RES	-0.392	0.25	-0.524	0.25	-0.270	0.43	-0.409	0.37
Lag $\Delta OIB $	0.004	0.00	0.004	0.00	0.003	0.00	0.004	0.00
Lag $\Delta\text{InstOwn}$			-0.005	0.27			-0.006	0.13
Lag $\Delta\text{LnNumest*100}$			-0.00001	0.98			-0.001	0.22
Adjusted R^2	0.167		0.163		0.170		0.164	

This table reports cross-sectional averages of time-series Granger causality regression results for NYSE-listed common stocks from January 2005 to December 2007. $\sigma(s)$ is the standard deviation of the discrepancies between log transaction price and the efficient price based on Hasbrouck (1993). $\sigma(p)$ is the standard deviation of intraday transaction prices. $|AR30|$ is the absolute value of the thirty-minute quote midpoint return autocorrelation. Shorting is shares shorted standardized by shares traded on a given stock day. VWAP is daily volume-weighted average price. Size is the market value of equity. Volume is daily share trading volume orthogonalized with respect to size. RES is daily value-weighted relative effective spreads. $|OIB|$ is the absolute value of daily share order imbalance standardized by share volume, where order imbalance is the difference between buyer-initiated trades and seller-initiated trades based on Lee and Ready's (1991) algorithm. InstOwn is the fraction of shares outstanding owned by institutions. NumAnalyst*100 is the number of sell-side analysts producing annual forecast of firm earnings (scaled up by 100). Ln represents the natural logarithm. Δ indicates first-order difference. Lag refers to the first-order lagged value. Daily variables are lagged one day, InstOwn is lagged one quarter, and NumAnalyst is lagged one month. Efficiency refers to $\sigma(s)/\sigma(p)$ or $\text{Ln}|AR30|$. The dependent variable is Δ Efficiency in Panel A and Δ Shorting in Panel B.

cross-sectional analysis and that they are not easily explainable using a reverse-causality story. It is also reassuring that the inferences from Table 2 hold in a time-series test using first differences.

Finally, some observations from additional tests (not reported) can shed additional light on the causality between shorting and efficiency. First, short sales became less constrained when the SEC removed the tick-test requirement for Reg SHO "pilot" stocks. To the extent that the Reg SHO selection of pilot firms is at least partly exogenous, these additional results are informative about causality. We find that the total effect of shorting on efficiency is lower

when shorting is more constrained. These findings make the reverse-causality explanation harder to sustain.

8. Conclusions

We examine how daily short-selling flow affects price discovery, the process by which new information becomes incorporated into security prices. We link short-selling activity to four different measures of relative informational efficiency and show that short sellers help keep prices in line with fundamentals. With more shorting, transaction prices follow a random walk more closely, monthly and annual price delays become smaller, post-earnings-announcement drift vanishes after negative earnings surprises, and extreme, non-information-based price movements become less pronounced. These results are fairly robust to different econometric approaches and model specifications, and we argue that reverse-causality explanations are hard to sustain.

Taken together, these different empirical approaches all suggest that short sellers' trading contributes significantly to price discovery in equity markets. Short selling is associated with more efficient pricing in the sense that prices appear to be closer to efficient or fundamental values when short sellers are more active. Our results suggest that the efficiency-enhancing effect of short sales affects prices quickly. Moreover, the magnitude of the effect of short sales on price efficiency is about the same as that associated with institutional holdings and is roughly three times that associated with analyst coverage. Conversely, we find no evidence that hints at price destabilizing or manipulative trading by short sellers.

Given the sustained worldwide regulatory interest in short selling and its effect on markets, our results have important implications, especially for recent regulatory actions that restrict short selling. Our results suggest that these restrictions constrain a particularly informed type of trading and are likely to impede the price-discovery function of equity markets.

Appendix

This Appendix presents the estimation of the pricing error. The notations closely follow those in Hasbrouck (1993). Hasbrouck assumes that the observed (log) transaction price at time t , p_t , can be decomposed into an efficient price, m_t , and the pricing error, s_t :

$$p_t = m_t + s_t, \tag{A1}$$

where m_t is defined as the security's expected value conditional on all available information at transaction time t . By definition, m_t only moves in response to new information and is assumed to follow a random walk. The pricing error s_t measures the deviation relative to the efficient price. It captures non-information-related market frictions (such as price discreteness and inventory control effects, etc.). s_t is assumed to be a zero-mean covariance-stationary process, and it can be serially correlated or correlated with the innovation from the random walk of efficient prices. Because the expected value of the deviations is zero, the standard deviation of the pricing error, $\sigma(s)$, measures the magnitude of deviations from the efficient price and can be interpreted as a measure of price efficiency for the purpose of assessing market quality.

In the empirical implementation, Hasbrouck (1993) estimates the following vector autoregression (VAR) system with five lags:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \dots + b_1 x_{t-1} + b_2 x_{t-2} + \dots + v_{1,t} \\ x_t &= c_1 r_{t-1} + c_2 r_{t-2} + \dots + d_1 x_{t-1} + d_2 x_{t-2} + \dots + v_{2,t}, \end{aligned} \quad (\text{A2})$$

where r_t is the difference in (log) prices p_t , and x_t is a column vector of trade-related variables: a trade sign indicator, signed trading volume, and signed square root of trading volume to allow for concavity between prices and trades. $v_{1,t}$ and $v_{2,t}$ are zero-mean, serially uncorrelated disturbances from the return equation and the trade equation, respectively.

The above VAR can be inverted to obtain its vector moving average (VMA) representation that expresses the variables in terms of contemporaneous and lagged disturbances:

$$\begin{aligned} r_t &= a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \dots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \dots \\ x_t &= c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \dots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \dots \end{aligned} \quad (\text{A3})$$

To calculate the pricing error, only the return equation in (A3) is used. The pricing error under Beveridge and Nelson's (1981) identification restriction can be expressed as

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \dots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \dots, \quad (\text{A4})$$

where $\alpha_j = -\sum_{k=j+1}^{\infty} a_k^*$, $\beta_j = -\sum_{k=j+1}^{\infty} b_k^*$. The variance of the pricing error is then computed as

$$\sigma_{(s)}^2 = \sum_{j=0}^{\infty} [\alpha_j, \beta_j] \text{Cov}(v) \begin{bmatrix} \alpha_j \\ \beta_j \end{bmatrix}. \quad (\text{A5})$$

In the estimation, all transactions in TAQ that satisfy certain criteria are included.²³ Following Hasbrouck (1993), we exclude overnight returns. We use Lee and Ready's (1991) algorithm to assign trade directions but make no time adjustment (Bessembinder 2003). To make comparisons across stocks meaningful, $\sigma(s)$ is scaled by the standard deviation of p_t , $\sigma(p)$, to control for cross-sectional differences in the return variance. This ratio $\sigma(s)/\sigma(p)$ reflects the proportion of deviations from the efficient price in the total variability of the observable transaction price process. Therefore, it serves as a natural measure of the informational efficiency of prices. Because the pricing error is inversely related to price efficiency, a smaller ratio means a more efficient stock price.²⁴ In the empirical analysis, this ratio is referred to as "pricing error" for brevity.

²³ Trades and quotes during regular market hours are used. For trades, we require that TAQ's CORR field is equal to zero and the COND field is either blank or equal to *, B, E, J, or K. Trades with nonpositive prices or sizes are eliminated. A trade with a price greater than 150% or less than 50% of the price of the previous trade is also excluded. For quotes, we include only those with positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. Quotes with nonpositive ask or bid prices or where the bid price is higher than the ask price are also excluded. A quote with an ask that is greater than 150% of the bid is also excluded. For each stock, we aggregate all trades during the same second then execute at the same price and retain only the last quote for every second if multiple quotes are reported.

²⁴ As pointed out by Hasbrouck (1993), if temporary deviations from the efficient price take too long to correct, pricing errors will be understated because deviations are erroneously attributed to changes in efficient price. This potential limitation is not a major concern in this study for two reasons. First, our analysis examines the relative efficiency of prices instead of price efficiency in an absolute sense. Second, the empirical tests focus on the cross-section of stocks, and this potential measurement error is unlikely to be highly systematic across stocks.

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