**Uptick rule, short selling and price efficiency**

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First draft: August 14, 2006

Preliminary

## Abstract

This paper investigates the effect on price efficiency of the SEC mandated suspension of the Uptick rule for a set of Pilot stocks listed on the NYSE. Relative to a matched sample, Pilot stocks experience increased shorting volume and wider spreads. More noticeably, these changes primarily come from small stocks, suggesting that the Uptick rule affects small stocks most heavily. Along the dimension of price discovery, we find no strong evidence that the suspension of the Uptick rule improves the price efficiency of Pilot stocks, indicating that the Uptick rule does not seriously constrain short sellers from trading on their information. We also provide direct evidence that short sellers can contribute to the informational efficiency of prices, regardless of whether the Uptick rule is in effect or not.

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## I. Introduction

Diamond and Verrecchia (1987) address the effect of short selling constraints on price reactions, liquidity and informational efficiency of securities. Specifically, they posit that short sale constraints can make security prices less informative in that it takes longer for the prices to adjust to new information. Short sales constraints include various forms such as direct monetary costs of borrowing shares, the difficulty of establishing a short position, potential short-squeeze, and the legal and institutional restrictions such as the Uptick rule (i.e. restricting traders from short selling on downticks or zero-minus ticks).

The purpose of this study is to empirically evaluate the effects of the Uptick rule on short sellers in price discovery. In particular, we focus on two questions. First, Diamond and Verrecchia (1987) imply that relaxing short sales constraints should improve the informational efficiency of prices because the private information that short sellers might have is incorporated into prices faster. We examine whether the Uptick rule imposes a serious constraint on the price discovery process. This analysis is partially motivated by the Regulation SHO (Reg SHO) Pilot program mandated by the SEC. As stated by the SEC, the purpose of the Reg SHO is to "evaluate the overall effectiveness of price test restrictions on short sales" and "study the effects of relatively unrestricted short selling on market volatility, price efficiency, and liquidity."[1] Thus, a better understanding

[1] Regulation SHO-Pilot Program (April 19 2005) at http://www.sec.gov/spotlight/shopilot.htm.

of the impact of the Uptick rule on price efficiency has important implications for policy makers and market regulators.

Second, with asymmetrically informed market participants, the process of incorporating private information is very important. Theoretical models such as Diamond and Verrecchia (1987) assume that short sellers are informed traders. However, traders can sell short for different motivations. Informed short sellers trade on their short-lived private information. Hedging, arbitrage-motivated trades, or short selling by market makers to fulfill their market-making obligations may not have as much information content. Thus shorting due to arbitrage and hedging activities in a stock may obscure the information content of short selling. Our second objective is to conduct a direct test on the informational role that short sellers might play in the price discovery process. Such an analysis adds to the current literature on short selling, which has primarily focused on the predictability of future returns from short selling or the mechanics of the lending market.[2]

This study is made possible using shorting data published by national stock exchanges required by the SEC for the Reg SHO Pilot. The SEC has chosen a subset of stocks with varying level of liquidity from the Russell 3000 index as of June 25, 2004 to be pilot stocks. For these pilot stocks, Reg SHO temporarily suspends the provisions of Rule 10a-1(a) under the SEC Act of 1934 and any short sale price test of any exchange or

[2]Figlewski (1981), Brent, Morse and Stice (1990), Senchack and Starks (1993), Choie and Hwang (1994), Aitken and et al. (1998), Dechow and et al. (2001), Desai and et al. (2002) , , Duffie, Garleanu and Pedersen (2002), Geczy, Musto and Reed (2002), Jones and Lamont (2002), Christophe, Ferri and Angel (2004), Reed (2003), Arnold, et al. (2005), Asquith, Pathak and Ritter (2005), Cohen, Diether and Malloy (2005), Nagel (2005), Boehme, Danielsen and Sorescu (2006), Boehmer, Jones and Zhang (2006), Desai, Krishnamurthy and Venkataraman (2006), to name a few.

national securities association.[3] In this study, we evaluate the effects of the Rule 10a-1 (i.e., the Uptick rule) on the price efficiency of stocks listed on the New York Stock Exchange (NYSE).

We use intraday data from TAQ to construct various measures of price efficiency. To evaluate the effects of the Uptick rule, we construct a matched sample of pilot and control stocks. We document several interesting findings. First, compared to control stocks, pilot stocks experience significantly more shorting after the Uptick rule was suspended. More interestingly, we show that the increase in shorting primarily comes from small stocks. Large-cap stocks experience no significant change in shorting volume. Thus the Uptick rule appears to impact small stocks most strongly.

Second, along the dimension of price efficiency (defined as how closely stock prices track a random walk), the overall evidence suggests that pilot stocks do not seem to experience significant improvement in informational efficiency following the suspension of the Uptick rule. In other words, the Uptick rule does not appear to be a serious constraint in the information incorporation process. We do not interpret this as strong evidence against Diamond and Verrecchia (1987). Rather, it could suggest that the Uptick rule may not be strongly binding on short sellers in this regard.

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[3] SEC selected the securities to be included in the Pilot by first excluding the 32 securities in the Russell 3000 index as of June 25, 2004 that are not Nasdaq national market securities ("NNM"), listed on the American Stock Exchange ("Amex"), or on the New York Stock Exchange ("NYSE"). Initial public offerings after April 30, 2004 are also excluded. The remaining securities are then sorted into three groups by marketplace -- Amex, Nasdaq NNM and NYSE -- and ranked the securities in each group by average daily dollar volume over the one year prior to the issuance of this order from highest to lowest for the period. In each ranked group, SEC selected every third stock to be pilot stocks where the first stock chosen was the 2nd, the next was the 5th, and so on. The remaining stocks are suggested to be used as the control group where the Uptick rule still applies. The Pilot stocks consist of 50% NYSE listed securities, 2.2% Amex listed securities, and 47.8% Nasdaq NNM securities. For more information about the Reg SHO, see SEC Release No. 50104/July 28, 2004.

Third, we find that following the suspension of Uptick rule, pilot stocks experience wider (not narrower) spreads. More strikingly, small stocks experience the most pronounced widening of spreads, while large stocks see no changes in the spreads. The widening of spreads following the relaxation of the Uptick rule appears to run counter to the predictions of Diamond and Verrecchia (1987). They argue that the imposition (not the relaxation) of shorting constraints is associated with wider bid-ask spreads. However, these results seem to suggest that short sellers tend to adopt different trading strategies in different regimes. The suspension of the Uptick rule enables short sellers to demand liquidity by placing market orders without restrictions. With the Uptick rule restriction, short sellers might have to place more limit orders on the ask side, thus providing liquidity to the market. Correspondingly, we also document that ask depths and net order imbalances decline following the suspension of the Uptick Rule. These results point to the adaptability of short sellers in different regimes. It would be interesting to see if these results reverse when the Reg SHO ends. In fact, Jones (2003) corroborates our findings and shows that market liquidity improved (i.e. spreads narrowed) when the no-downtick rule was imposed in October 1931.

Higher execution costs such as widened spreads following the Reg SHO might offer a partial explanation for the insignificant change in price efficiency. On one hand, short sellers face less constraint due to the suspension of the Uptick rule, which might improve price efficiency. On the other hand, larger transaction costs make arbitrage more costly, thus hindering price discovery. These two effects counteract each other, leading to no improvement in price efficiency.

Lastly, multivariate analysis presents some evidence that short sellers can contribute to the informational efficiency of prices, regardless of whether the Uptick rule is in effect or not. Specifically, stocks with more shorting activity have higher relative price efficiency. This result is robust to various econometric methodologies and model specifications. The general picture that emerges from these results suggests that short sellers can facilitate price discovery by making stock prices follow more closely to a random walk. Our empirical evidence on the informational role that short sellers might play in price discovery complements recent literature on the informativeness of short sellers in return predictions (Dechow and et al. (2001), Desai and et al. (2002), Asquith, Pathak and Ritter (2004), Boehmer, Jones and Zhang (2006)).

This paper is most closely related to two other independent studies on Reg SHO by Diether, Lee and Werner (2005) and Alexander and Peterson (2006). Diether, Lee and Werner (2005) document that after the suspension of the Uptick rule, pilot stocks on the NYSE have seen higher shorting volume, wider spreads and smaller offer sizes. Contrary to Diether, Lee and Werner (2005), Alexander and Peterson (2006) find that pilot stocks have similar shorting volume. Our size-stratified analysis reconciles this difference by showing that small stocks are impacted the most by the Uptick rule, and their difference could be due to sample construction.

The remainder of the paper is organized as follows. Section II describes the data and construction of variables. Section III presents event analysis of the Reg SHO Pilot on price efficiency. Section IV analyzes the relation between price efficiency and short selling in a multivariate context. Section V concludes the paper.

## II. Data and constructions of variables

### II.1 The sample

There are several potential event dates associated with the Reg SHO Pilot program.[4] For the purpose of this study, what matters most is the actual date when traders can carry out shorting without the Uptick restriction. We therefore use May 2, 2005 as the event date in our analysis. Our sample period covers four months before (January 2005 – April 2005) and four months after the event date (May 2005 - August 2005).[5]

The SEC selected the securities to be included in the Pilot in the Russell 3000 index as of June 25, 2004 (see footnote 4 for detailed selection process). We include securities that are members of both Russell 3000 index of 2004 and 2005 as our initial sample. This requirement intends to eliminate potential confounding effects from index deletion/addition. Next, because we are primarily interested in the effects of the Uptick rule, we include only domestic, common stocks listed on the NYSE through matching the initial sample to the securities in the Center for Research in Security Prices (CRSP).[6] We obtain consolidated trading volume, price, return, and market capitalization from the CRSP. Further, if a stock's month-end price during the sample period is above $900, it is

[4] Reg SHO came into effect on September 7, 2004 and the compliance to the rules was originally intended to start on January 3, 2005. But the pilot was postponed until May 2, 2005. The new terminate date of the Pilot is set to be August 6, 2007, instead of April 28, 2006. See Securities Exchange Act of 1934 Release No. 53684.

[5] The sample period starts from January 2005 because the NYSE starts to publish shorting data from that month.

[6] Stocks listed on the Amex are excluded because a large majority of exchange listed stocks in the Russell 3000 are from the NYSE.

excluded from the sample to avoid potential influence of unduly high price.[7] This process yields a sample of 415 (831) pilot (control) stocks.

We aggregate the shorting transaction data published by the NYSE into monthly data. Short trades that occur outside the normal trading hours are excluded. In addition, we compute monthly price efficiency measures and other market quality measures from the NYSE's Trade and Quote (TAQ) database (see Section III for details). These two datasets are then matched with the above sample.

Among these stocks that have survived the above data filters (i.e., 415 (831) pilot (control) stocks), we then try to match each pilot stock with a control stock along three dimensions based on the pre-event period averages: market capitalization (MktCap), month-end share price (Prc) and consolidated trading volume (Volume). Specifically, for each pilot stock, we first try to find a control stock that is within 120% and 80% of each of these dimensions, and then select the control stock that produces the minimum pairwise absolute matching error.[8] Such a matched sample would ensure that the effects detected do not simply arise from market-wide changes in informational efficiency and liquidity that coincide with the implementation of the Reg SHO. The final sample contains 332 matched pilot stocks.

Table 1 reports the summary statistics of the final matched pairs. We can see that the control group is very similar to the pilot stocks in size, price, and average trading activity. The distribution of matching errors suggests that these two groups of stocks are matched well.

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[7] WPO is excluded.

[8] Matching error = $|MktCap_p - MktCap_c| / MktCap_p + |Prc_p - Prc_c| / Prc_p + |Volume_p - Volume_c| / Volume_p$

## II.2 Measures of price efficiency

We construct three measures of price efficiency to test the effects of the suspension of the Uptick rule. The definition of price efficiency here refers to how closely observable transaction prices follow a random walk. The more efficient the prices are, the more random the sequence of price changes is. And this dynamic process is the direct result of many active traders attempting to profit from their information (Lo (2004)). We use intraday transaction data to compute these price efficiency measures. Such an approach would allow us to factor into the continuous nature of the information flow and order flow. Chordia, Roll and Subrahmanyam (2005) suggest that astute traders who follow the market intently generally eliminate potential price inefficiency within 30 minutes.

We calculate (1) pricing errors suggested in Hasbrouck (1993), (2) the absolute value of 30-(60-) minute quote midpoint return autocorrelations, and (3) the distance between unit and 30- (60-) minute vs.10-minute midpoint return variance ratios to proxy for the informational efficiency of prices.

### Pricing errors

The first proxy for price efficiency is the pricing errors in Hasbrouck (1993). To study price discovery, he focuses on the "efficient" price of a security defined as its expected value conditional on a given information set. Since the efficient price is not observable, Hasbrouck uses information about trade size and execution price for all transactions to conduct a variance decomposition procedure through a dynamic Vector

AutoRegression (VAR) model to separate the efficient price from price deviations that are unrelated to new information. The distinction between the two components is that information shocks should have persistent impact on prices while market imperfections should have only transient effects.

Assuming that the observed (log) transaction price, $p_t$, can be decomposed into an efficient price, $m_t$, and a pricing error, $s_t$, we have

$p_t = m_t + s_t$.

where $m_t$, by definition, only moves in response to new information and is assumed to follow a random walk. The pricing error $s_t$ reflects non-information related frictions in the market (such as price discreteness and inventory control effects). It is assumed to be a zero-mean covariance-stationary process. Because the expected value of the deviations is assumed by the procedure to be zero, the standard deviation, V(s), measures the magnitude of price deviation from efficient price, and can be interpreted as a measure of price efficiency. We also standardize V(s) by the standard deviation of $p_t$,, V(p), to control for cross-sectional differences in the return variance. This ratio reflects the proportion of deviations from the efficient price in the total variability of the observable transaction price process. Therefore, it is a natural measure of the informational efficiency of prices.[9] Because the pricing error is inversely related to price efficiency, the smaller the ratio, the more efficient the price is. In the following text, we use V(s)/V(p) to refer to this ratio.

We estimate the pricing errors for each stock on a monthly basis based on the TAQ data. We obtain all primary market prices and quotes from TAQ that satisfy certain

[9] Boehmer, Saar and Yu (2005) apply a similar methodology to study the effect of Openbook on the NYSE. Boehmer and Kelley (2006) find that institutions contribute to price efficiency using similar approaches.

criteria.[10] For each stock, we aggregate all trades during the same second that execute at the same price and retain only the last quote for every second if multiple quotes were issued. Following Hasbrouck (1993), we estimate a VAR system with five lags and four equations for (1) the difference in (log) price, (2) a trade sign indicator, (3) signed trading volume, and (4) signed square root of trading volume that allows for a concave relationship between prices and the trade series. Overnight changes are not included. We follow Lee and Ready (1991) to assign trade directions but make no time adjustment (Bessembinder (2003), Peterson and Sirri (2003)). The VAR can be estimated and then inverted to obtain the VMA representation, from which we estimate V(s). We hypothesize that if the Uptick rule imposes a serious constraint on short sellers, the pricing errors should be smaller following the suspension of the rule.

### Autocorrelations

We also use the quote midpoint return autocorrelation as an alternative measure of price efficiency. If the quote midpoint is the market's best estimate of the equilibrium value of the stock at every point in time, a more efficient price suggests that the quote midpoints are closer to a random walk and are expected to exhibit less autocorrelation in both positive and negative directions.

[10] We use trades and quotes only during regular market hours. 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. We eliminate trades with non-positive prices or sizes. We also exclude a trade if its price is greater than 150% or less than 50% of the price of the previous trade. We include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. We exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. We also exclude a quote if the ask is greater than 150% of the bid.

We compute monthly quote midpoint return autocorrelations measured over 30- (60-) minute intervals, excluding overnight returns.[11] We examine the absolute value of the autocorrelations because we are interested in testing how closely the return process resembles a random walk, which is characterized by zero autocorrelations. We hypothesize that the absolute value of these autocorrelations should become smaller following the implementation of the Reg SHO if short sellers find the Uptick rule a material constraint on them.

**Variance Ratios**

Prior literature also uses variance ratios to test the efficiency of security prices (Hasbrouck and Schwartz (1988) ). If a stock's price follows a random walk, then the variance of the random error is linear in the time frame over which prices are observed. Simply, the ratio of long-term to short-term return variances should be one relative to a unit of time. Specifically, we define the variance ratio of quote midpoint returns as:

$$VR\ (30,10) = \sigma^2_{\text{30-minute}} / \sigma^2_{\text{10-minute}} *3\ ,$$

$$VR\ (60,10) = \sigma^2_{\text{60-minute}} / \sigma^2_{\text{10-minute}} *6$$

The variance ratios are computed monthly for each stock. Because we are more interested in the deviation of prices from the efficient price in either direction, we use the absolute value of the difference between the variance ratio and one. In other words, we use

[11] Chordia, Roll and Subrahmanyam (2005) show prices are not efficient within 30-minute intervals. We thus use 30- and 60-minute intervals. We use both the absolute value of autocorrelations as well as their natural logs in our analysis. Results are qualitatively the same and available upon request.

|VR(30,10) –1| and |VR(60,10) –1| in the empirical tests. If the suspension of the Uptick rule improves price efficiency, these two measures should be smaller in magnitude.

## III. Event study on Reg SHO

In this section, we examine the effect of the Uptick rule on price efficiency. As discussed earlier, we choose May 2, 2005 as the event date. To mitigate possible time-trends in the data, we examine the changes between post- and pre-event periods in the differences between pilot stocks and their matched control stocks.

### III.1 Relative shorting activities

Table 2 compares the shorting activity between the matched pilot and control stocks. We use two measures of relative shorting activity to make the numbers comparable across stocks with different trading activity. RelativeShorting1 is shares shorted divided by consolidated trading volume; RelativeShorting2 is shares shorted divided by its trading volume on the NYSE only. Panel A shows that, in the pre-event period, pilot (control) stocks have an average of 20.6% (20.2%) relative to the consolidated trading volume, and 24.9% (24.6%) relative to NYSE volume. Compared to an average of about 13% (of NYSE SuperDot trading volume) documented in Boehmer, Jones and Zhang (2006) during January 2000 – April 2004, the statistics presented here suggests a tremendous increase in shorting activity on the NYSE overtime. Note that pilot stocks do not differ significantly from control stocks in the relative shorting intensity during the pre-Reg SHO period.

Did relative shorting activity increase following the Reg SHO? We observe that average shorting in pilot stocks has significantly increased during the post-event period. Shorting in pilot stocks climbs to 21.7 (27.1%) relative to the consolidated (NYSE) volume, whereas shorting in control stocks has slightly declined. The changes from the pre-event to post-event in the differences between pilot and control stocks are all significant. These increased shorting in pilot stocks suggests that the Uptick rule does seem to constrain short sellers to some extent.

Prior literature suggests that the effects of short sale constraints tend to be more pronounced on small stocks (D'Avolio (2002), Geczy, Musto and Reed (2002), Jones (2003), Asquith, Pathak and Ritter (2004), Nagel (2005)). We further stratify the sample into size quintiles based on the pre-event average of market capitalization of pilot stocks to examine cross-sectional variation in shorting activity.  Panel B reveals a very interesting pattern on shorting volume. Specifically, larger pilot stocks experience no significant increase in shorting activity. In sharp contrast, the increased shorting demand primarily comes from smaller stocks. For example, the post-pre difference between pilot and control stocks has increased by 2.3 %( 3.5%) for the smallest group. This interesting observation suggests that the Uptick rule is more binding on small stocks, consistent with prior work. These results help reconcile some differences between Diether, Lee and Werner (2005) and Alexander and Peterson (2006). The former finds that relative shorting in pilot stocks has increased following the Reg SHO, whereas the latter reports no change in short trading volume. The evidence here suggests that there could be a “size effect" in the Uptick rule.[12] One possible reason might be that the matching procedure in Alexander and Peterson (2006) produces a sample of relatively large stocks, compared to the sample in Diether, Lee and Werner (2005).

### III.2 Price efficiency

Diamond and Verrecchia (1987) posit that short sale constraints can make prices less informative. Therefore, relaxing these constraints should improve the informational efficiency of prices because the private information that short sellers might have is incorporated into prices faster. We next turn our attention to the effect of Uptick rule on price efficiency, the primary focus of this study. If the rule is a serious constraint on short sellers, we might expect to see improvement in price efficiency after the rule was suspended.

Table 3 compares the pricing errors between pilot stocks and their matched control stocks. We report both the natural log of Hasbrouck (1993) pricing error, LnV(s) and the scaled pricing error, V(s)/V(p). As discussed earlier, smaller pricing errors suggest that prices are relatively more efficient. On the whole, we find that the direction of changes in both measures following the Reg SHO is consistent with more efficient prices, but the results are rather weak as the differences of difference are not significant at all. The evidence suggests that the restriction of the Uptick rule does not seem to have a material effect on price efficiency.

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[12] Jones (2003) finds the short sales restriction in October 1931 affects small stock liquidity more than large stock liquidity.

Panel B examines the cross-sectional variation in the pricing errors across size quintiles. Notice that both pricing errors decline monotonically as stocks get larger, suggesting that larger stocks are more efficiently priced. This should not be surprising because large stocks tend to have more analyst coverage, more transparent information environment and more active trading. Examining the changes in differences, we find no significant improvement in price efficiency across all size groups. Thus, the Uptick restriction does not seem to be able to hinder price discovery. We point out that these results do not necessarily mean that they are inconsistent with Diamond and Verrecchia (1987), rather, they could suggest that  the Uptick rule does not seriously constrain short sellers from trading on their information.

Table 4 examines the price efficiency using the absolute values of 30- (60-) minute quote midpoint return autocorrelations of pilot and control stocks. Panel A shows that neither the 30-minute nor 60-minute return autocorrelations are reduced significantly following the implementation of the Reg SHO. The size-stratified analysis in Panel B presents a similar picture. The evidence here echoes the results in Table 3, suggesting that price discovery process is not significantly hampered by the Uptick rule.

Table 5 reports the variance ratio analysis. Consistent with the results based on pricing errors and return autocorrelations, Panel A shows that pilot stocks do not experience a significant reduction in their deviation from unit. A closer look at size-stratified groups in Panel B produces similar findings.

Overall, the Uptick rule does not seem to have a material effect on the informational efficiency of prices. There is no significant improvement in price efficiency following the suspension of the rule. These results indicate that in the regime of minimum tick size of $0.01, it is much easier for a short to trade on an Uptick. It is thus doubtful whether the Uptick rule is as effective as it was in the old regimes with larger minimum tick requirements.

### III.3 Liquidity

The purpose of the SEC's Reg SHO program also includes evaluation on liquidity. Liquidity might affect price efficiency. For example, one commonly used measure of liquidity is spreads. Intuitively, high transaction costs such as wide spreads can potentially limit arbitragers to take positions if potential profits that the informational advantage can bring are less than the transaction costs. Diamond and Verrecchia (1987) show that the imposition of short selling constraints should be associated with worsened liquidity such as wider spreads.

Table 6 compares market quality measures between pilot and control stocks. We present results on time-weighted relative quoted spreads (RQS), trade-weighted relative effective spreads (RES), order imbalances relative to the consolidated trading volume (RelativeOIB1), order imbalances relative to NYSE trading volume (RelativeOIB2), and quoted bid (ask) depths. RQS is the difference between the bid-ask spread divided by the quote midpoint. RES is twice the distance between the execution price and the prevailing quote midpoint scaled by the prevailing quote midpoint. Order imbalances are the differences between buy and sell volume where buys and sells are assigned based on the algorithm in Lee and Ready (1991). They are then scaled by the consolidated (NYSE) volume. Quoted bid (ask) depth is the quoted depth on the bid (ask) side measured in number of shares.

Panel A shows that following the implementation of Reg SHO, quoted and effective spreads widen for pilot stocks and at the same time, quoted offer size for pilot stocks has declined. The widening of spreads appears to run counter to the predictions of Diamond and Verrecchia (1987). However, these results seem to suggest that short sellers tend to adopt different trading strategies in different regimes. The suspension of the Uptick rule enables short sellers to demand liquidity without restrictions by placing more market orders. With the Uptick rule, short sellers might have to use limit orders on the ask side, thus providing liquidity to the market. Interestingly, we also find that the ask depth declines following the suspension of the Uptick Rule. These two results seem to suggest the adaptability in trading strategies of short sellers in different regimes that are not modeled in Diamond and Verrecchia (1987). It would be interesting to see if these results reverse when the Reg SHO pilot terminates. In fact, Jones (2003) finds that market liquidity improved when the no-downtick rule in October 1931 was imposed.

Higher trading costs such as widened spreads following the Reg SHO might serve as a partial explanation for the insignificant change in price efficiency. On one hand, short sellers face relatively less constraint due to the suspension of the Uptick rule, which might help improve price efficiency. On the other hand, higher transaction costs tend to make arbitrages more costly, thus hindering price discovery. These two factors work from opposite directions, leading to no change in the informational efficiency of price.

Panel B investigates the market quality across size quintiles. A noticeable pattern emerges. Smallest stocks are affected most by the Uptick rule. Their time-weighted relative quoted spreads and trade-weighted effective spreads have increased significantly by 2.3 and 2.0 basis points, respectively. Large-cap stocks, on the other hand, do not experience much change in the spreads. This liquidity pattern corresponds to the shorting demand pattern in Table 2. Both patterns reflect that the Uptick rule does not affect all stocks equally; rather, small stocks are most sensitive to the Uptick rule. One plausible explanation could be that small stocks are harder to short and are more sensitive to liquidity shocks.

The spreads pattern here and the relative shorting pattern in Table 2 complement some results in Diether, Lee and Werner (2005). They show that spreads widen most for pilot stocks with the highest shorting intensity. We point out that it is small stocks that have experienced the largest increase in shorting intensity and the corresponding widening in spreads. Such a "size effect" associated with the Uptick rule might be helpful to regulators in assessing the efficacy of the rule.

### III.4 Intraday volatility

Regulators have expressed concerns about the effect of short selling on stock price volatility. Table 7 compares the intraday volatility between pilot and control stocks. We use two measures to proxy for intraday volatility. Volatility1 is the difference between intraday maximum price and minimum price of a stock scaled by its daily

VWAP. Volatility2 is the log standard deviation of the intraday transaction prices. They are calculated from TAQ.

Panel A shows that the suspension of the Uptick rule does not induce more intraday volatility, as the changes in differences between pilot and control stocks are insignificant. Panel B reports these volatility measures by size quintiles. It is not surprising that intraday volatility monotonically decreases with firm size. More important, we document no significant changes in intraday volatility across all size groups. Thus the suspension of the Uptick rule does not seem to destabilize the stock market. Alexander and Peterson (2006) document similar results using different measures of volatility.

To sum up, results in this section suggest that the Uptick rule does not seem to impose a serious constraint on short sellers in the price discovery process. Short sellers seem to be able to surmount the Uptick restrictions in trading on private information they might possess. Interestingly, the suspension of the rule seems to be associated with different trading strategies in order submission of short sellers, causing shifts in liquidity provision dynamics. Further, we present evidence that the Uptick rule has different effects across stocks. Small stocks are impacted most by the rule as they experience the most pronounced increase in relative shorting activity and spreads. Such a “size effect” raises the concern of whether one-size-fits-all is the best approach in setting short-selling restrictions.

## IV. Multivariate cross-sectional analysis

Prior empirical literature has shown that short sellers are informed traders in terms of predicting future returns. Boehmer, Jones and Zhang (2006) document that stocks heavily shorted significantly underperform those lightly shorted at various short-term horizons. Their results suggest that short sellers might possess important information and can potentially improve price efficiency through their trades. We now conduct direct tests to examine whether short selling can improve price efficiency.

Out of concerns with econometric issues, we perform the regression analysis of shorting on price efficiency using daily data. First, it is more appropriate to perform a stock fixed-effects analysis given the nature of the panel data. A pooled OLS would generate biased estimates. However, a fixed-effects estimation using monthly data is not optimal because for each stock we only have 7 data points (due to the use of lagged variables) in its time series. Second, Fama and MacBeth (1973) regressions on price efficiency can be performed more effectively using daily data. We cannot conduct monthly Fama-McBeth regressions because it would only generate 7 time-series of cross-sectional regression coefficients. Such a small number might distort the t-statistics to make meaningful inferences.

We focus on the effect of shorting on the pricing errors in the daily analysis. We do not use |AR30| (|AR60|) or |VR (30, 10)-1| (|VR (60, 10|) in the daily analysis because we cannot obtain reliable estimates of these measures due to too few return intervals within a trading day. Because very few time-series observations in a VAR might distort the calculation of pricing errors, we require a minimum of 100 trades per stock day in our daily analysis. In addition, pricing errors greater than 1 are excluded.

We are primarily interested in the effect of short selling on price efficiency, after controlling for other explanatory variables. We include the following control variables. Post is an indicator variable equal to one after May 2, 2005 and zero before that date to control for the period when Reg SHO is in effective. PilotPost is a dummy variable equal to one if it is after the Reg SHO implementation date and the stock is a pilot and equal to zero otherwise.[13] We also control for a stock's daily VWAP, share volume, market capitalization, and relative effective spreads. We use the lagged explanatory variables in the regressions to mitigate any potential effect of changes in price efficiency on these contemporaneous explanatory variables.

Table 8 reports the panel regression results with stock fixed-effects estimation. Model 1 presents a significant negative coefficient of shorting, indicating that more shorting is associated with higher informational efficiency (i.e. smaller pricing errors). Other control variables show signs consistent with previous studies. Prices are more informationally efficient for more actively traded stocks. Higher trading costs faced by traders, measured by the relative effective spreads, can limit arbitrageurs' profits, and thus are associated with larger pricing errors.

Boehmer and Kelley (2006) find that institutional investors improve price efficiency. We thus control for institutional ownership obtained from the 13F filings in the CDA Spectrum database. Because analyst coverage might improve a firm's

[13] We do not include a dummy for pilot stocks because it is time-invariant and would be dropped out with the fixed-effects estimation.

informational environment, we also control for the number of analysts following a firm obtained from I/B/E/S. Model 2 shows that even after controlling for institutional ownership and analysts, short sellers still seem to be able to contribute to price discovery. Institutions and analysts have negative coefficients, consistent with Boehmer and Kelley (2006).

Table 9 reports Fama and MacBeth (1973) regressions. Specifically, we conduct cross-sectional analysis on a daily basis and report the time-series averages of the regression coefficients and t-statistics based on Newey-West standard errors to correct for potential autocorrelations.[14] Model 1 reports a significant negative coefficient of relative shorting, confirming that shorting is informative. Institutional ownership and the number of analysts are controlled for in Model 2 and we document a consistently negative coefficient of short selling on pricing errors.

To sum up, the multivariate analysis presents direct evidence that short sellers can improve price efficiency by making stock prices follow more closely to a random walk. The evidence on more price efficiency associated with more shorting adds to the literature and complements current literature on the informativeness of short sellers.

## V. Conclusions

The Reg SHO Pilot program mandated by the SEC gives us an opportunity to examine the effects on the informational efficiency of prices of the suspension of the Uptick rule. The question of price efficiency is particularly interesting and important

[14] We have used various lags for the Newey-West standard errors. Results are not sensitive to the number of lags used. We report those adjusted with 20 lags.

because one of the stated goals of the SEC Reg SHO pilot program is to examine the effects of relatively unrestricted short selling on price efficiency. Theoretical work by Diamond and Verrecchia (1987) suggests that short sale constraints hinder the incorporation process of private information. The first objective of this paper is to empirically examine the effects on price efficiency of short sale constraints by focusing on the Uptick rule on a set of stocks listed on the NYSE.

We construct a matched sample of pilot and control stocks. The main findings can be summarized as follows. First, relative to control stocks, pilot stocks exempt from the Uptick rule experience significant increases in short selling after the Uptick rule was suspended. More interestingly, the increase in shorting for those stocks primarily comes from small-cap stocks. Large- cap pilot stocks have similar shorting level to that of control stocks. Thus the Uptick rule appears to affect small stocks most strongly.

Second, pilot stocks on average do not seem to experience significant improvement in informational efficiency following the suspension of the Uptick rule. This indicates that the Uptick rule is not a serious constraint on short sellers in the price discovery process.

Third, after the suspension of Uptick rule, pilot stocks experience wider (not narrower) spreads. Further, only the spreads of small-cap stocks widen significantly; large stocks do not see a significant increase in spreads. These results seem to suggest that short sellers tend to adopt different trading strategies in different regimes. The suspension of the Uptick rule enables short sellers to demand liquidity without restrictions by placing more market orders. With the Uptick rule, short sellers might have to place more limit orders on the ask side, thus providing liquidity to the market. Consequently, there is a shift in liquidity demand/supply dynamics following the Reg SHO. Interestingly, we also find that the ask depth declines following the suspension of the Uptick Rule. These two results seem to suggest the adaptability of short sellers in different regimes.

This paper then tries to address a broader question of whether short sellers can improve the informational efficiency of prices. The general picture that emerges from multivariate analysis suggests that short sellers contribute to price efficiency by making stocks follow more closely to a random walk. Our results complement current literature on the informativeness of short selling which has primarily focused on the predictability of future returns at various horizons.

Our results have some policy implications. The significant increase of shorting volume and spreads in small stocks suggests that the Uptick rule has different effects across stocks. Large stocks, on the other hand, are not affected in these respects. This "size effect" may aid regulators in making decisions about whether the Uptick rule should be removed, at least in part, for some securities.

Along the dimension of price efficiency, the suspension of the Uptick rule does not seem to significantly improve price efficiency. At the same time, intraday volatility in the unrestricted regime does not worsen, either. These results indicate that in the new regime of the minimum tick size of $0.01, it is much easier for a short to trade on an Uptick. It is thus doubtful whether the Uptick rule is as effective as it was in the old regimes with larger minimum tick requirements.

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**Table 1. Sample Description**

This table presents some summary statistics of the matched pilot stocks and control stocks listed on the NYSE before the Reg SHO implementation date (05/02/2005). The sample is based on domestic common stocks listed on NYSE between January 2005-August 2005. Each pilot stock is matched with a control stock along three dimensions based on the pre-event period averages: market capitalization (MktCap), month-end share price (Prc) and consolidated trading volume (Volume). Specifically, for each pilot stock, we first try to find a control stock that is within 120% and 80% of each of these dimensions, and then select the control stock that produces the minimum pairwise absolute matching error. Matching error = $|MktCap_p - MktCap_c| / MktCap_p + |Prc_p - Prc_c| / Prc_p + |Volume_p - Volume_c| / Volume_p$, where $p$ refers to pilot stocks and $c$ refers to control stocks.

**Panel A: Summary statistics of the matched sample.**

| | **Mean** | |
|---|---|---|
| | **Pilot** | **Control** |
| Market cap. ($ billions) | 6.95 | 6.90 |
| Price | 36.09 | 35.49 |
| Volume(millions) | 196.91 | 195.07 |

**Panel B: Distribution of matching errors**

| | **mean** | **median** | **min** | **max** |
|---|---|---|---|---|
| matching errors | 0.2193398 | 0.2134606 | 0.0268665 | 0.5053792 |

**Table 2. Relative shorting activity of pilot and control stocks before and after the RegSHO**

This table compares the relative shorting activities between the matched pilot stocks and control stocks from January 2005 through August 2005. Pre refers to January 2005-April 2005. Post refers to May 2005 to August 2005. Diff = p-c is the difference between pilot and matched control stock. Difference of differences are the changes in the differences between pilot and control stocks. RelativeShorting1 is the shares shorted scaled by consolidated share volume. RelativeShorting2 is the shares shorted divided by NYSE share volume.

| | pre | | | | post | | | | post-pre | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **pilot** | **control** | **diff=p-c** | **t** | **pilot** | **control** | **diff=p-c** | **t** | **Difference of differences** | **t** | **p** |
| **Panel A: Relative shorting activities** | | | | | | | | | | | |
| RelativeShorting1 | 20.6% | 20.2% | 0.4% | 1.12 | 21.7% | 19.5% | 2.2% | 6.27 | 1.8% | 3.71 | 0.000 |
| RelativeShorting2 | 24.9% | 24.6% | 0.3% | 0.79 | 27.1% | 24.4% | 2.7% | 6.38 | 2.3% | 4.05 | 0.000 |
| **Panel B: Relative shorting activities by size quintile** | | | | | | | | | | | |
| **Size group 1 (smallest)** | | | | | | | | | | | |
| RelativeShorting1 | 20.9% | 20.4% | 0.5% | 0.56 | 22.8% | 20.0% | 2.8% | 3.37 | 2.3% | 3.71 | 0.000 |
| RelativeShorting2 | 25.4% | 24.9% | 0.5% | 0.53 | 29.1% | 25.1% | 4.0% | 3.99 | 3.5% | 4.05 | 0.000 |
| **Size group 2** | | | | | | | | | | | |
| RelativeShorting1 | 22.6% | 22.1% | 0.5% | 0.58 | 23.9% | 21.2% | 2.7% | 3.34 | 2.2% | 1.98 | 0.050 |
| RelativeShorting2 | 27.2% | 26.3% | 0.8% | 0.92 | 29.4% | 26.4% | 3.0% | 3.29 | 2.2% | 1.70 | 0.092 |
| **Size group 3** | | | | | | | | | | | |
| RelativeShorting1 | 21.2% | 22.0% | -0.8% | -1.05 | 22.5% | 21.0% | 1.5% | 1.9 | 2.3% | 2.10 | 0.038 |
| RelativeShorting2 | 25.2% | 26.5% | -1.2% | -1.52 | 27.7% | 26.0% | 1.7% | 1.98 | 3.0% | 2.48 | 0.014 |
| **Size group 4** | | | | | | | | | | | |
| RelativeShorting1 | 20.1% | 19.6% | 0.5% | 0.7 | 20.8% | 18.9% | 1.8% | 2.27 | 1.3% | 1.14 | 0.258 |
| RelativeShorting2 | 24.1% | 23.9% | 0.3% | 0.27 | 25.5% | 23.7% | 1.7% | 1.93 | 1.5% | 1.13 | 0.260 |
| **Size group 5 (largest)** | | | | | | | | | | | |
| RelativeShorting1 | 18.1% | 16.9% | 1.2% | 1.88 | 18.5% | 16.2% | 2.3% | 3.12 | 1.0% | 1.05 | 0.296 |
| RelativeShorting2 | 22.6% | 21.4% | 1.2% | 1.44 | 23.9% | 21.0% | 2.9% | 2.95 | 1.6% | 1.27 | 0.206 |

**Table 3. Pricing errors of pilot and control stocks before and after the RegSHO**

This table compare the pricing errors of pilot stocks to those of control stocks during sample period between January 2005 through August 2005. Pre refers to January 2005-April 2005. Post refers to May 2005 to August 2005. Diff = p-c is the difference between pilot and matched control stock. Difference of differences are the changes in the differences between pilot and control stocks. V(s) is the pricing error (i.e. the standard deviation of the discrepancies between log quote midpoint and the efficient (random walk) price) and V(p) is the standard deviation of intraday transaction prices. V(s) is calculated following Hasbrouck (1993). Ln refers to the natural logarithm.

| | pre | | | | post | | | | post-pre | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **pilot** | **control** | **diff=p-c** | **t** | **pilot** | **control** | **diff=p-c** | **t** | **Difference of differences** | **t** | **p** |
| **Panel A: pricing errors** | | | | | | | | | | | |
| LnVs | 0.6604 | 0.6487 | 0.0117 | 0.73 | 0.5721 | 0.5853 | -0.0132 | -0.92 | -0.0249 | -1.16 | 0.247 |
| V(s)/V(p) | 0.0099 | 0.0100 | -0.0001 | -0.33 | 0.0095 | 0.0101 | -0.0006 | -1.5 | -0.0005 | -1.05 | 0.296 |
| **Panel B: pricing errors by size quintile** | | | | | | | | | | | |
| **Size group 1 (smallest)** | | | | | | | | | | | |
| LnVs | 1.4272 | 1.4516 | -0.0244 | -0.65 | 1.3331 | 1.3609 | -0.0278 | -0.71 | -0.0034 | -1.16 | 0.247 |
| V(s)/V(p) | 0.0169 | 0.0158 | 0.0011 | 1.12 | 0.0151 | 0.0153 | -0.0002 | -0.23 | -0.0013 | -1.05 | 0.296 |
| **Size group 2** | | | | | | | | | | | |
| LnVs | 0.9645 | 0.9406 | 0.0239 | 0.67 | 0.8480 | 0.8510 | -0.0030 | -0.09 | -0.0269 | -0.56 | 0.579 |
| V(s)/V(p) | 0.0111 | 0.0124 | -0.0014 | -1.41 | 0.0104 | 0.0117 | -0.0012 | -0.94 | 0.0001 | 0.08 | 0.936 |
| **Size group 3** | | | | | | | | | | | |
| LnVs | 0.6125 | 0.5910 | 0.0214 | 0.59 | 0.5530 | 0.5440 | 0.0091 | 0.34 | -0.0124 | -0.27 | 0.785 |
| V(s)/V(p) | 0.0092 | 0.0086 | 0.0006 | 1.43 | 0.0089 | 0.0088 | 0.0001 | 0.16 | -0.0005 | -0.65 | 0.518 |
| **Size group 4** | | | | | | | | | | | |
| LnVs | 0.2914 | 0.3215 | -0.0301 | -0.85 | 0.2031 | 0.2654 | -0.0623 | -1.68 | -0.0322 | -0.63 | 0.530 |
| V(s)/V(p) | 0.0068 | 0.0072 | -0.0004 | -1.41 | 0.0072 | 0.0075 | -0.0003 | -0.52 | 0.0001 | 0.21 | 0.834 |
| **Size group 5 (largest)** | | | | | | | | | | | |
| LnVs | 0.0072 | -0.0608 | 0.0680 | 2.08 | -0.0752 | -0.0938 | 0.0186 | 0.85 | -0.0493 | -1.25 | 0.212 |
| V(s)/V(p) | 0.0054 | 0.0057 | -0.0003 | -1.18 | 0.0057 | 0.0073 | -0.0016 | -1.36 | -0.0013 | -1.07 | 0.289 |

**Table 4. Intraday return autocorrelations of pilot and control stocks before and after the RegSHO**

This table compare the absolute value of the intraday autocorrelations of pilot stocks to those of control stocks during sample period between January 2005 through August 2005. Pre refers to January 2005-April 2005. Post refers to May 2005 to August 2005. Diff = p-c is the difference between pilot and matched control stock. Difference of differences are the changes in the differences between pilot and control stocks. absAR30 (absAR60) is the absolute value of 30-minute(60-minute) quote midpoint return autocorrelation.

| | **pre** | | | | **post** | | | | **post-pre** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **pilot** | **control** | **diff=p-c** | **t** | **pilot** | **control** | **diff=p-c** | **t** | **Difference of differences** | **t** | **p** |
| **Panel A: absolute value of autocorrelations** | | | | | | | | | | | |
| absAR30 | 0.0732 | 0.0740 | -0.0008 | -0.36 | 0.0741 | 0.0722 | 0.0018 | 0.8 | 0.0026 | 0.82 | 0.410 |
| absAR60 | 0.0898 | 0.0921 | -0.0023 | -0.86 | 0.0858 | 0.0856 | 0.0002 | 0.09 | 0.0025 | 0.68 | 0.499 |
| **Panel B: absolute value of autocorrelations by size quintile** | | | | | | | | | | | |
| **Size group 1 (smallest)** | | | | | | | | | | | |
| absAR30 | 0.0812 | 0.0871 | -0.0059 | -1.06 | 0.0833 | 0.0789 | 0.0044 | 0.77 | 0.0103 | 0.82 | 0.410 |
| absAR60 | 0.0982 | 0.1012 | -0.0030 | -0.43 | 0.0948 | 0.0842 | 0.0106 | 1.45 | 0.0136 | 0.68 | 0.499 |
| **Size group 2** | | | | | | | | | | | |
| absAR30 | 0.0755 | 0.0730 | 0.0025 | 0.49 | 0.0755 | 0.0762 | -0.0007 | -0.12 | -0.0032 | -0.43 | 0.671 |
| absAR60 | 0.0877 | 0.1009 | -0.0132 | -2.54 | 0.0875 | 0.0914 | -0.0040 | -0.82 | 0.0093 | 1.30 | 0.195 |
| **Size group 3** | | | | | | | | | | | |
| absAR30 | 0.0722 | 0.0734 | -0.0012 | -0.23 | 0.0707 | 0.0753 | -0.0047 | -0.97 | -0.0035 | -0.50 | 0.618 |
| absAR60 | 0.0905 | 0.0900 | 0.0005 | 0.1 | 0.0824 | 0.0858 | -0.0033 | -0.61 | -0.0039 | -0.50 | 0.617 |
| **Size group 4** | | | | | | | | | | | |
| absAR30 | 0.0661 | 0.0726 | -0.0066 | -1.37 | 0.0747 | 0.0663 | 0.0085 | 1.69 | 0.0150 | 2.17 | 0.032 |
| absAR60 | 0.0884 | 0.0933 | -0.0049 | -0.76 | 0.0828 | 0.0833 | -0.0005 | -0.09 | 0.0044 | 0.51 | 0.613 |
| **Size group 5 (largest)** | | | | | | | | | | | |
| absAR30 | 0.0712 | 0.0640 | 0.0072 | 1.7 | 0.0661 | 0.0645 | 0.0016 | 0.36 | -0.0056 | -0.91 | 0.363 |
| absAR60 | 0.0841 | 0.0748 | 0.0093 | 1.64 | 0.0814 | 0.0830 | -0.0016 | -0.29 | -0.0109 | -1.40 | 0.165 |

**Table 5. Variance ratios of pilot and control stocks before and after the RegSHO**

This table compare the variance ratios of pilot stocks to those of control stocks during sample period between January 2005 through August 2005. Pre refers to January 2005-April 2005. Post refers to May 2005 to August 2005. Diff = p-c is the difference between pilot and matched control stock. Difference of differences are the changes in the differences between pilot and control stocks. |VR(30,10) -1| (|VR(60,10)-1|) is the absolute value of the distance between one and the variance ratio of 30-minute (60-minute) over 10-minute quote midpoint returns.

| | **pre** | | | | **post** | | | | **post-pre** | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **pilot** | **control** | **diff=p-c** | **t** | **pilot** | **control** | **diff=p-c** | **t** | **Difference of differences** | **t** | **p** |
| **Panel A: Variance ratios** | | | | | | | | | | | |
| \|VR(30, 10) - 1\| | 0.1641 | 0.1567 | 0.0073 | 1.51 | 0.1758 | 0.1641 | 0.0118 | 2.64 | 0.0044 | 0.68 | 0.500 |
| \|VR(60, 10) - 1\| | 0.3160 | 0.3071 | 0.0089 | 1.46 | 0.3414 | 0.3186 | 0.0228 | 3.79 | 0.0139 | 1.62 | 0.106 |
| **Panel B: Variance ratios by size quintile** | | | | | | | | | | | |
| **Size group 1 (smallest)** | | | | | | | | | | | |
| \|VR(30, 10) - 1\| | 0.1684 | 0.1656 | 0.0028 | 0.21 | 0.1756 | 0.1449 | 0.0306 | 2.64 | 0.0278 | 0.68 | 0.500 |
| \|VR(60, 10) - 1\| | 0.3112 | 0.3168 | -0.0056 | -0.33 | 0.3273 | 0.2816 | 0.0457 | 2.83 | 0.0512 | 1.62 | 0.106 |
| **Size group 2** | | | | | | | | | | | |
| \|VR(30, 10) - 1\| | 0.1653 | 0.1768 | -0.0115 | -1.19 | 0.1827 | 0.1645 | 0.0182 | 2.06 | 0.0296 | 2.26 | 0.025 |
| \|VR(60, 10) - 1\| | 0.3333 | 0.3348 | -0.0015 | -0.11 | 0.3546 | 0.3319 | 0.0227 | 1.81 | 0.0242 | 1.31 | 0.193 |
| **Size group 3** | | | | | | | | | | | |
| \|VR(30, 10) - 1\| | 0.1731 | 0.1489 | 0.0242 | 2.19 | 0.1707 | 0.1605 | 0.0102 | 1.01 | -0.0140 | -0.93 | 0.353 |
| \|VR(60, 10) - 1\| | 0.3259 | 0.3010 | 0.0250 | 2.12 | 0.3400 | 0.3192 | 0.0208 | 1.55 | -0.0042 | -0.23 | 0.816 |
| **Size group 4** | | | | | | | | | | | |
| \|VR(30, 10) - 1\| | 0.1684 | 0.1568 | 0.0117 | 1.25 | 0.1826 | 0.1911 | -0.0085 | -0.76 | -0.0202 | -1.39 | 0.167 |
| \|VR(60, 10) - 1\| | 0.3193 | 0.3016 | 0.0177 | 1.52 | 0.3466 | 0.3401 | 0.0065 | 0.44 | -0.0112 | -0.60 | 0.551 |
| **Size group 5 (largest)** | | | | | | | | | | | |
| \|VR(30, 10) - 1\| | 0.1449 | 0.1353 | 0.0096 | 0.95 | 0.1674 | 0.1589 | 0.0085 | 1.17 | -0.0011 | -0.08 | 0.933 |
| \|VR(60, 10) - 1\| | 0.2898 | 0.2809 | 0.0089 | 0.65 | 0.3381 | 0.3196 | 0.0184 | 1.96 | 0.0095 | 0.58 | 0.566 |

**Table 6. Spreads, depths and order imbalances of pilot and control stocks before and after the RegSHO**

This table compare spreads, quoted depths and order imbalances between pilot stocks with control stocks during sample period between January 2005 through August 2005. Pre refers to January 2005-April 2005. Post refers to May 2005 to August 2005. Diff = p-c is the difference between pilot and matched control stock. Difference of differences are the changes in the differences between pilot and control stocks. RQS is the average of daily time-weighted relative quoted spread. RES is the daily average of trade-weighted relative effective spreads. BidSize (OfferSize) is the average of relative quoted depth. RelativeOIB1 is the difference between NYSE buy and sell share volume scaled by total consolidated trading volume. RelativeOIB2 is the difference between NYSE buy and sell share volume scaled by NYSE trading volume.

| | pre | | | | post | | | | post-pre | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | pilot | control | diff=p-c | t | pilot | control | diff=p-c | t | Difference of differences | t | p |
| **Panel A: spreads, order imbalances and depths** | | | | | | | | | | | |
| RQS | 0.1102% | 0.1134% | -0.0031% | -1.55 | 0.1115% | 0.1070% | 0.0045% | 2.01 | 0.0077% | 2.53 | 0.012 |
| RES | 0.0887% | 0.0909% | -0.0022% | -1.3 | 0.0879% | 0.0839% | 0.0040% | 2.36 | 0.0062% | 2.60 | 0.009 |
| RelativeOIB1 | 0.0835 | 0.0798 | 0.0037 | 1.41 | 0.0077 | 0.0839 | -0.0761 | -29.33 | -0.0798 | -21.58 | 0.000 |
| RelativeOIB2 | 0.1014 | 0.0976 | 0.0038 | 1.17 | 0.0100 | 0.1052 | -0.0952 | -28.93 | -0.0990 | -21.44 | 0.000 |
| BidSize | 7.9525 | 8.2273 | -0.2749 | -1.37 | 8.0097 | 9.9945 | -1.9848 | -1.4 | -1.7099 | -1.20 | 0.232 |
| OfferSize | 10.7235 | 11.1865 | -0.4631 | -1.61 | 7.5049 | 12.2623 | -4.7574 | -6.28 | -4.2943 | -5.30 | 0.000 |
| **Panel B: spreads, order imbalances and depths by size quintile** | | | | | | | | | | | |
| **Size group 1( Smallest)** | | | | | | | | | | | |
| RQS | 0.2164% | 0.2362% | -0.0198% | -2.38 | 0.2268% | 0.2235% | 0.0034% | 0.35 | 0.0232% | 2.53 | 0.012 |
| RES | 0.1703% | 0.1847% | -0.0144% | -2.12 | 0.1752% | 0.1693% | 0.0059% | 0.82 | 0.0203% | 2.60 | 0.009 |
| RelativeOIB1 | 0.0672 | 0.0638 | 0.0034 | 0.5 | 0.0023 | 0.0833 | -0.0810 | -11.97 | -0.0844 | -21.58 | 0.000 |
| RelativeOIB2 | 0.0816 | 0.0775 | 0.0042 | 0.5 | 0.0033 | 0.1045 | -0.1011 | -12.07 | -0.1053 | -21.44 | 0.000 |
| BidSize | 6.8957 | 6.9011 | -0.0055 | -0.02 | 5.8485 | 6.2539 | -0.4054 | -1.8 | -0.3999 | -1.20 | 0.232 |
| OfferSize | 7.9056 | 8.6032 | -0.6976 | -1.27 | 5.6398 | 8.5649 | -2.9251 | -4.31 | -2.2275 | -5.30 | 0.000 |
| **Size group 2** | | | | | | | | | | | |
| RQS | 0.1322% | 0.1290% | 0.0032% | 0.85 | 0.1291% | 0.1244% | 0.0047% | 1.05 | 0.0015% | 0.26 | 0.796 |
| RES | 0.1046% | 0.1027% | 0.0019% | 0.57 | 0.0993% | 0.0966% | 0.0027% | 0.78 | 0.0008% | 0.17 | 0.866 |
| RelativeOIB1 | 0.0832 | 0.0788 | 0.0044 | 0.75 | 0.0115 | 0.0905 | -0.0790 | -12.47 | -0.0834 | -9.66 | 0.000 |
| RelativeOIB2 | 0.1006 | 0.0942 | 0.0063 | 0.91 | 0.0144 | 0.1130 | -0.0986 | -12.66 | -0.1049 | -10.05 | 0.000 |
| BidSize | 6.2450 | 6.4102 | -0.1652 | -0.53 | 5.9578 | 6.6892 | -0.7314 | -2.06 | -0.5662 | -1.20 | 0.231 |
| OfferSize | 8.4809 | 9.3052 | -0.8243 | -1.4 | 6.1133 | 9.3330 | -3.2197 | -3.82 | -2.3954 | -2.33 | 0.021 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Size group 3** | | | | | | | | | | | | |
| RQS | 0.0923% | 0.0937% | -0.0014% | -0.45 | 0.0921% | 0.0857% | 0.0064% | 2.19 | 0.0078% | 1.83 | 0.070 |
| RES | 0.0760% | 0.0765% | -0.0005% | -0.19 | 0.0742% | 0.0689% | 0.0052% | 2.1 | 0.0057% | 1.61 | 0.110 |
| RelativeOIB1 | 0.0850 | 0.0914 | -0.0064 | -1.14 | 0.0128 | 0.0907 | -0.0779 | -15.82 | -0.0715 | -9.62 | 0.000 |
| RelativeOIB2 | 0.1018 | 0.1103 | -0.0085 | -1.32 | 0.0164 | 0.1127 | -0.0963 | -15.88 | -0.0878 | -9.91 | 0.000 |
| BidSize | 7.2601 | 6.6845 | 0.5756 | 2.14 | 6.5735 | 7.2327 | -0.6592 | -0.95 | -1.2348 | -1.65 | 0.101 |
| OfferSize | 10.3445 | 9.4877 | 0.8568 | 1.86 | 6.6604 | 9.9603 | -3.2999 | -4.67 | -4.1567 | -4.93 | 0.000 |
| **Size group 4** | | | | | | | | | | | | |
| RES | 0.0452% | 0.0455% | -0.0004% | -0.23 | 0.0442% | 0.0423% | 0.0019% | 1.21 | 0.0022% | 1.03 | 0.305 |
| RES | 0.0529% | 0.0532% | -0.0003% | -0.18 | 0.0516% | 0.0491% | 0.0026% | 1.39 | 0.0029% | 1.13 | 0.262 |
| RelativeOIB1 | 0.0952 | 0.0882 | 0.0070 | 1.25 | 0.0047 | 0.0848 | -0.0801 | -14.22 | -0.0872 | -10.97 | 0.000 |
| RelativeOIB2 | 0.1144 | 0.1081 | 0.0063 | 0.87 | 0.0062 | 0.1059 | -0.0997 | -14.12 | -0.1060 | -10.48 | 0.000 |
| BidSize | 7.8099 | 8.2892 | -0.4793 | -1.41 | 10.8721 | 8.3367 | 2.5354 | 0.71 | 3.0147 | 0.84 | 0.401 |
| OfferSize | 10.9710 | 11.9616 | -0.9906 | -1.18 | 8.9622 | 12.0059 | -3.0436 | -1.94 | -2.0530 | -1.15 | 0.252 |
| **Size group 5 (largest)** | | | | | | | | | | | | |
| RQS | 0.0465% | 0.0442% | 0.0023% | 2.15 | 0.0464% | 0.0418% | 0.0047% | 5.1 | 0.0024% | 1.71 | 0.089 |
| RES | 0.0401% | 0.0377% | 0.0024% | 2.33 | 0.0396% | 0.0357% | 0.0039% | 4.84 | 0.0015% | 1.15 | 0.250 |
| RelativeOIB1 | 0.0866 | 0.0766 | 0.0100 | 1.8 | 0.0074 | 0.0700 | -0.0626 | -12.52 | -0.0726 | -9.71 | 0.000 |
| RelativeOIB2 | 0.1083 | 0.0976 | 0.0106 | 1.48 | 0.0098 | 0.0900 | -0.0802 | -11.11 | -0.0908 | -8.91 | 0.000 |
| BidSize | 11.5797 | 12.8783 | -1.2985 | -1.68 | 10.7842 | 21.5351 | -10.7509 | -1.79 | -9.4524 | -1.56 | 0.120 |
| OfferSize | 15.9454 | 16.5916 | -0.6462 | -0.94 | 10.1479 | 21.4959 | -11.3480 | -3.66 | -10.7019 | -3.37 | 0.001 |

**Table 7. Intraday volatility of pilot and control stocks before and after the RegSHO**

This table compare intraday volatility between pilot stocks with control stocks during sample period between January 2005 through August 2005. Pre refers to January 2005-April 2005. Post refers to May 2005 to August 2005. Diff = p-c is the difference between pilot and matched control stock. Difference of differences are the changes in the differences between pilot and control stocks. Volatility1 is the intraday price range between the highest and lowest transaction prices standardized by daily VWAP. Volatility2 is the log of intraday transaction price standard deviation.

| | pre | | | | post | | | | post-pre | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | **pilot** | **control** | **diff=p-c** | **t** | **pilot** | **control** | **diff=p-c** | **t** | **Difference of differences** | **t** | **p** |
| **Panel A: Intraday volatility** | | | | | | | | | | | |
| Volatility1 | 0.0226 | 0.0223 | 0.0004 | 1.02 | 0.0208 | 0.0204 | 0.0004 | 1.11 | 0.0000 | 0.05 | 0.962 |
| Volatility2 | 5.5089 | 5.4714 | 0.0375 | 1.57 | 5.4492 | 5.4289 | 0.0203 | 0.74 | -0.0173 | -0.48 | 0.634 |
| **Panel B: Intraday volatility by size quintile** | | | | | | | | | | | |
| **Size group 1 (smallest)** | | | | | | | | | | | |
| Volatility1 | 0.0279 | 0.0285 | -0.0006 | -0.59 | 0.0272 | 0.0266 | 0.0005 | 0.54 | 0.0011 | 0.05 | 0.962 |
| Volatility2 | 5.7091 | 5.7669 | -0.0578 | -1.15 | 5.6976 | 5.7275 | -0.0299 | -0.61 | 0.0279 | -0.48 | 0.634 |
| **Size group 2** | | | | | | | | | | | |
| Volatility1 | 0.0253 | 0.0242 | 0.0011 | 1.18 | 0.0234 | 0.0228 | 0.0006 | 0.69 | -0.0005 | -0.38 | 0.704 |
| Volatility2 | 5.6119 | 5.5109 | 0.1010 | 1.61 | 5.5892 | 5.5114 | 0.0778 | 1.1 | -0.0231 | -0.24 | 0.807 |
| **Size group 3** | | | | | | | | | | | |
| Volatility1 | 0.0213 | 0.0221 | -0.0008 | -1.08 | 0.0197 | 0.0201 | -0.0004 | -0.64 | 0.0003 | 0.33 | 0.740 |
| Volatility2 | 5.4544 | 5.4901 | -0.0356 | -0.66 | 5.4401 | 5.4387 | 0.0014 | 0.02 | 0.0370 | 0.44 | 0.660 |
| **Size group 4** | | | | | | | | | | | |
| Volatility1 | 0.0200 | 0.0193 | 0.0007 | 1.35 | 0.0175 | 0.0173 | 0.0002 | 0.32 | -0.0005 | -0.64 | 0.521 |
| Volatility2 | 5.4281 | 5.3726 | 0.0555 | 1.21 | 5.3103 | 5.3025 | 0.0078 | 0.14 | -0.0477 | -0.66 | 0.513 |
| **Size group 5 (largest)** | | | | | | | | | | | |
| Volatility1 | 0.0186 | 0.0173 | 0.0012 | 2.06 | 0.0164 | 0.0154 | 0.0010 | 1.81 | -0.0002 | -0.30 | 0.768 |
| Volatility2 | 5.3407 | 5.2174 | 0.1234 | 2.46 | 5.2085 | 5.1649 | 0.0435 | 0.68 | -0.0798 | -0.99 | 0.326 |

**Table 8. Panel regressions of daily shorting on price efficiency**

This table presents panel regression results with stock fixed-effects for a sample of NYSE-listed domestic common stocks from 01/03/2005 through 08/27/2005. The dependent variable is the pricing error, V(s)/V(p), calculated following Hasbrouck (1993). V(s) is the standard deviation of the discrepancies between log quote midpoint and the efficicent (random walk) price and V(p) is the standard deviation of intraday transaction prices. Independent variables include the following. LagShorting is the first lagged shorting relative to total trading volume. DV is the dependent variable. VWAP, Volume, Size, RES is the daily VWAP, share volume, market capitalization, and the relative effective spreads, respectively. Post is a dummy equal to 1 if after May 2, 2005 and 0 before that date. PilotPost is a dummy variable equal to one if the stock is a pilot stock and the date is after May 2, 2005 and 0 otherwise. InstOwn is the previous quarter-end percentage institutional ownership. NumAnalyst*100 is previous month's number of analysts following the stock (scaled up by 100). Lag indicates the first lag. Ln refers to the natural logarithm.

| | **Model 1** | | | **Model 2** | | |
|---|---|---|---|---|---|---|
| | **Coef.** | **t** | **P>\|t\|** | **Coef.** | **t** | **P>\|t\|** |
| Intercept | 0.4039 | 15.94 | 0.000 | 0.4685 | 16.54 | 0.000 |
| LagShorting | -0.0138 | -10.65 | 0.000 | -0.0130 | -9.79 | 0.000 |
| LagLnVWAP | 0.0027 | 1.44 | 0.151 | 0.0038 | 1.89 | 0.059 |
| LagLnVolume | -0.0115 | -38.49 | 0.000 | -0.0109 | -35.87 | 0.000 |
| LagLnSize | -0.0131 | -6.61 | 0.000 | -0.0139 | -6.37 | 0.000 |
| LagRES | 8.4879 | 15.64 | 0.000 | 9.6069 | 16.68 | 0.000 |
| Post | 0.0037 | 10.82 | 0.000 | 0.0033 | 9.5 | 0.000 |
| PilotPost | -0.0016 | -2.79 | 0.005 | -0.0010 | -1.66 | 0.097 |
| LagDV | 0.1465 | 62.45 | 0.000 | 0.1437 | 57.81 | 0.000 |
| InstOwn | | | | -0.0380 | -15.91 | 0.000 |
| LnNumAnalyst*100 | | | | -0.0057 | -7.35 | 0.000 |
| | | | | | | |
| R2: within | 0.04 | | | 0.05 | | |
| between | 0.69 | | | 0.71 | | |
| overall | 0.36 | | | 0.36 | | |
| No. of obs. | 199135 | | | 177195 | | |

**Table 9: Cross-sectional effect of daily shorting on price efficiency**

Fama-McBeth regressions of daily shorting on price eficiency for a sample of NYSE-listed domestic common stocks, 01/03/2005 - 08/27/2005. The dependent variable is the pricing error, V(s)/V(p). V(s) is the standard deviation of the discrepancies between log quote midpoint and the efficicent price and V(p) is the standard deviation of intraday transaction prices. Independent variables include the following. Shorting is the daily shorting volume relative to total trading volume. VWAP, Volume, Size, RES are the daily VWAP, share volume, market capitalization, and the relative effective spreads, respectively. Pilot is a dummy variable equal to one if the stock is a pilot stock and 0 otherwise. InstOwn is the previous quarter-end percentage institutional ownership. NumAnalyst*100 is previous month's number of analysts following the stock (scaled up by 100). DV is the dependent variable. Lag indicates the first lag. Ln refers to the natural logarithm. The t-statistics are based on the time-series of coefficient estimates from the daily cross-sectional regressions using Newey-West standard errors with 20 lags.

| | **Coef.** | **t** | **P>\|t\|** | **Coef.** | **t** | **P>\|t\|** |
|---|---|---|---|---|---|---|
| Intercept | 0.2045 | 39.83 | 0.000 | 0.2312 | 49.25 | 0.000 |
| LagShorting | -0.0157 | -5.85 | 0.000 | -0.0131 | -5.46 | 0.000 |
| LagLnVWAP | -0.0094 | -20.98 | 0.000 | -0.0084 | -27.92 | 0.000 |
| LagLnVolume | -0.0168 | -21.53 | 0.000 | -0.0143 | -20.83 | 0.000 |
| LagRES | 31.4849 | 17.97 | 0.000 | 29.9917 | 17.19 | 0.000 |
| LagLnSize | 0.0056 | 10.82 | 0.000 | 0.0039 | 7.16 | 0.000 |
| Pilot | -0.0036 | -11.65 | 0.000 | -0.0028 | -9.92 | 0.000 |
| LagDV | 0.3394 | 25.76 | 0.000 | 0.3232 | 29.91 | 0.000 |
| InstOwn | | | | -0.0179 | -8.66 | 0.000 |
| LnNumAnalyst*100 | | | | -0.0032 | -7.03 | 0.000 |
| | | | | | | |
| Number of stocks | 1211 | | | 1080 | | |
| adj. R2 | 0.45 | | | 0.449 | | |