Information Acquisition and Short Selling *

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First Draft: March 2018

Current Draft: April 2018

Abstract: Sophisticated traders, like short sellers, may deter information acquisition by less sophisticated traders. We measure information acquisition as the contribution of earnings announcements to volatility—when earnings announcements account for a greater share of volatility, then less of the information is priced prior to announcements. We use the SEC's short sale pilot program and find that information acquisition falls when short selling is easier and the effect reverses after the pilot. We find symmetric results for good and bad news, consistent with information acquisition as opposed to a direct effect of short-selling activity. Further, we study the mechanism by combining the pilot program with the discontinuity in institutional ownership around the Russell 1000/2000 threshold. Pilot (but not control) stocks suffer particularly large losses in information acquisition where institutional ownership increases around the threshold, consistent with a complementarity between lendable shares and easier short selling rules. Our results suggest that short sellers, while informed themselves, can decrease price efficiency by deterring the information acquisition of others.

* We have benefited from discussions with Vikas Agarwal, Hitesh Doshi, Tom George, Kris Jacobs, and participants at the University of Houston bag lunch.

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I. Introduction

The price discovery process has two major components: (1) the information acquisition process, during which traders gather information, and (2) the trading mechanisms that allow traders to incorporate information into stock prices, conditional on the information being acquired in the first place. Theoretically, more efficient trading mechanisms have an ambiguous effect on information acquisition (Grossman and Stiglitz (1980)). On the one hand, efficient trading reduces the cost of trading on information, thus increasing incentives for information acquisition. On the other hand, efficient trading reduces mispricing, which reduces incentives for information acquisition.[1] The picture is further complicated when the most sophisticated traders are not the same people acquiring fundamental information. In this case, more efficient trading mechanisms allows the sophisticated traders to more quickly incorporate public information or even extract the information from those who collected it--e.g. they can "back-run" (Yang and Zhu (2017))— thus reducing the incentives for non-sophisticated traders to collect information.[2] The net effect of efficient trading on information acquisition therefore depends on how much fundamental analysis the sophisticated traders undertake.

Short selling is an ideal laboratory to study information acquisition. There is a consensus that short sellers are sophisticated and have information.[3] However, it is less clear what type of information short sellers have, or how they obtain it. Engelberg, Reed, and Ringgenberg (2012) argue that short sellers primarily process information rather than collect it. When information is more quickly incorporated into prices by short sellers, non-short sellers have less incentive to collect information ex-ante. Boehmer, Jones, Wu, and Zhang (2018), on the other hand, argue that short sellers have private information about firm

[1] In the extreme case of Grossman and Stiglitz (1980), all market participants solve for the rational expectations equilibrium so that prices reflect all acquired information, thus undermining any incentive for information acquisition.

[2] Consider post-earnings announcement drift (PEAD), a robust phenomenon generally attributed to delayed information incorporation. PEAD encourages information acquisition by giving informed agents more time to profit from their information. If sophisticated traders reduce PEAD by more quickly incorporating information, then informed agents will be more constrained and thus have less incentive to collect information ex-ante.

[3] For example, see Cohen, Diether, and Malloy (2007) Boehmer, Jones, and Zhang (2008) Diether, Lee, and Werner (2009), Boehmer and Wu (2012), and Rapach, Ringgenberg and Zhou (2016).

fundamentals beyond analysts' knowledge. The net effect of short-selling on information acquisition is therefore the difference between the direct acquisition of information by short-sellers and the deterrent effect from superior information processing.

Our measure of information acquisition is motivated by Weller (2017) and Jiang, Shen, Wermers, and Yao (2017). In particular, we measure the contribution of earnings announcements to stock return variance. For each earnings announcement, we calculate realized variance (RV) by summing the squared daily returns from one month prior to the announcement to two days after the announcement. We denote this variable, calculated using closing prices from 22 days before the announcement to 2 days after, as RV[-22,2]. Likewise, we calculate the sum of squared daily returns from the announcement day to 2 days after, and denote this RV[-1,2]. The ratio RV[-1,2]/RV[-22,2] is therefore the contribution of earnings news to volatility, and is inversely related to the amount of information incorporated prior to announcement. When the information in the earnings announcement is already incorporated in the stock price prior to the announcement, then the ratio will approach zero ("high information acquisition"); conversely, if none of the earnings information is incorporated in the price prior to the announcement, then the ratio will move toward one ("low information acquisition"). Our measure resembles Weller (2017), who measures information acquisition as the contribution of earnings announcements to stock returns over the same month window as us. By using variance rather than returns, our measure treats return reversals and continuations at announcement symmetrically—the unpriced information at announcement could be positively or negatively related to the information that has already been incorporated. In this latter regard, we resemble Jiang, Shen, Wermers, and Yao (2017), who measure "information intensity" as the contribution of jumps to variance. Jiang, Shen, Wermers, and Yao (2017) estimate jumps non-parametrically; we essentially treat earnings announcements as jumps and proceed analogously.

We use the SEC's short sale pilot to study the effect of short selling on information acquisition. The pilot program made short-selling easier for every third stock in the Russell 3000 by removing the uptick rule. The uptick rule prevents short-selling after a price decline—shorting is only allowed after prices tick up. The pilot program's exogenous removal of the uptick rule resulted in a substantial increase in shorting activity, and has consequently been used extensively to study the causal effect of short selling on a variety of outcomes (e.g. Alexander and Peterson (2008), Diether, Lee, and Werner (2009), and De Angelis, Grullon, and Michenaud (2017)). We implement the same research design by comparing pilot stocks with the rest of the Russell 3000.

We find that short-selling results in a modest reduction of information acquisition. Across our whole sample, earnings announcements contribute an extra 1.5 p.p. to the realized variance in the month around announcement. The magnitude equates to 5.5% of the sample average, and 6.7% of its standard deviation. We also see the reversal of the effect after the uptick rule is removed for all stocks in mid-2007—that is, the pilot stocks had less information acquisition than the control stocks during the pilot, but the control stocks moved toward the pilot stocks when the uptick rule was removed for the control group. The drop in information acquisition is symmetric for good and bad earnings releases. This symmetry is consistent with short-sellers deterring information acquisition because the acquirers do not know ex-ante whether the information will be good or bad. At the same time, the symmetry is not consistent with a direct effect of short-selling, which should be more pronounced for bad news.[4]

Exploring the dynamics around earnings announcements, we see that our effect is driven by the day of the earnings announcement. The extra share of volatility at announcement partially comes from a reduction in the share of volatility attributed to days 3-5 prior to the announcement, which is when short-sellers are particularly active (Christophe, Ferri, and Angel (2004)). These dynamics support the idea that some information acquisition is deterred because short-sellers will be there to capture the information. As a result, a relatively larger share of the information is priced when it is publicly released. We also find that the couple days after announcement contribute less to volatility for the pilot stocks, which is consistent with previous findings on the effect of short-selling on post-earnings announcement drift (Reed (2007)).

[4] The symmetry also implies that our results are not being driven by the strategically imprecise disclosure of bad news documented in Li and Zhang (2015)

Like Diether, Lee, and Werner (2009), we do not see a statistically significant increase in volatility either at announcement or over the announcement month—only the share of volatility at announcement increases. Nor do we find an effect of short-selling on the probability of an earnings surprise. We corroborate the literature and find that volumes increase when short-selling is allowed, but the fraction of volume after announcement does not change.[5] It does not seem, therefore, that the presence of short-selling affects the total information released by the firm at announcement; rather, the information is disproportionately priced after a public announcement. We should note, however, that our results are driven by the top 75% of earnings surprises and not small surprises or neutral announcements. This can reconcile our results with Fang, Huang, and Karpoff (2016), who find reductions in discretionary accruals and the probability of marginally beating earnings targets for pilot stocks—short sellers process accounting information well, but in doing so deter information acquisition regarding bigger earnings-related news.

We next turn to the heterogeneity in the result. There are two reasons the uptick rule may have varying effects for different stocks: first, the uptick rule may not equally bind everywhere, and second, even when the uptick rule binds it may have different effects on information acquisition. Regarding the first consideration, the uptick rule may have only a mild distortionary effect or none at all for many stocks (Alexander and Peterson (2008), Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009)). We study changes in institutional ownership during the pilot program to explore where the uptick rule may bind. There is a tight connection between short selling and institutional ownership. Nagel (2005) shows that institutional ownership is a proxy for relaxed constraints on short-selling because institutions lend shares to earn fees. If the uptick rule binds short sellers, then its repeal acts as a shock to the demand for lendable shares. In the simple case where the uptick rule only causes this shift in demand, then the new equilibrium will move up the supply curve, leading to more institutional ownership. Thus, a change in institutional ownership during the pilot program is evidence that the uptick rule was binding. We find that

[5] Bollerslev, Li, and Xue (2017) argue that a decrease in the volume-volatility elasticity reflects more disagreement in prices. The fact that we find, for pilot stocks, no change in the share of volume at announcement, but an increase in the share of volatility is therefore consistent with increased disagreement in prices when shorting is easier (Miller (1977)).

pilot stocks experienced an increase of 1.5 p.p in institutional ownership during the program. This is consistent with institutions choosing to hold securities which can be more profitably lent. The change in institutional ownership is concentrated in the bottom two size terciles. Large stocks, on the other hand, do not appear as constrained by the uptick rule, perhaps because the market is sufficiently liquid or because traders can form synthetic shorts in the option market.

Even if the uptick rule binds for the two smaller terciles, the effect of the rule on information acquisition may vary. We again split our sample into terciles by size and find that the change in information acquisition is driven by the middle tercile. The suspension of the uptick rule has a slightly negative effect on information acquisition for the top and bottom tercile, while the effect for the middle tercile is nearly three times as large as the coefficient for the entire sample and is statistically different from the other terciles. The uptick rule may not bind for the biggest stocks; the smallest stocks, on the other hand, may have more substantial information asymmetries that render the uptick rule of second- or third-order importance to information acquisition. The uptick rule seems to have actual bite in the middle of the size distribution.

Finally, to hone in on the mechanism, we study the interaction of institutional ownership and the uptick rule. The uptick rule is not the only constraint facing short sellers—they also need to find shares to borrow. If the repeal of the uptick rule deters information acquisition because of an increase in short sellers, then the effect should be larger when accompanied by a simultaneous increase in lendable shares. But institutional ownership is endogenous and informed (Duong, Huszar, Tan, and Zhang (2017)), making its connection to short-selling difficult to interpret.

We use the discontinuity in institutional ownership around the Russell 1000/2000 index reconstitution during the pilot program to more carefully study the interaction of short selling and institutional ownership. In particular, we implement the design of Chang, Hong, and Liskovich (2014) separately for pilot and control stocks during the pilot program. For control stocks, we find that institutional ownership falls when included in the Russell 1000, albeit statistically insignificant. This is in line with previous findings in the literature. For pilot stocks, however, we see the reverse—institutional ownership increases upon inclusion in the Russell 1000. At this threshold, funds that track the indices have to rebalance their holdings. Our results suggest that these funds strategically avoid pilot stocks when index weights are high. Institutions may anticipate negative price effects from short selling, or may be wary of bear raids (e.g. De Angelis, Grullon, and Michenaud (2017)).

With these results on institutional ownership at the Russell threshold, we next turn to information intensity—again measured as the contribution of earnings announcements to volatility. Information intensity increases by 4-5.5 pp upon inclusion in the Russell 1000. This is a threefold increase from the baseline difference-in-difference estimates, and occurs when institutional ownership discontinuously increases. In other words, there is a very strong interaction between institutional ownership and the removal of the uptick rule that deters information acquisition. Institutional ownership by itself, however, does not seem to deter information acquisition—the sign of our coefficient flips (but is statistically insignificant) when performing the regression discontinuity for control stocks—consistent with Boone and White (2015). To our knowledge, we are the first paper to combine the short-sale pilot with the Russell discontinuity, which provides a fortuitous way to study the strong interaction of short selling and institutional ownership.

Taken together, our results imply that the presence of short sellers deters information acquisition regarding firm fundamentals. The suspension of the uptick rule leads to a large increase in shorting activity, which corresponds to an increased contribution of earnings announcements to stock variance. Further, the effect is an order of magnitude larger when institutional ownership increases. Potential information acquirers therefore appear particularly hesitant to collect information when sophisticated short sellers are able to easily and cheaply trade. In pointing out a dark side of short-selling on price discovery, our results are contrary to the literature which—excepting evidence for bear raids in Cohen, Diether, and Malloy (2014), Grullon, Michenaud, and Weston (2015), and De Angelis, Grullon, and Michenaud (2017)—consistently points to the benefits of short-selling.

II. Related literature

Empirical studies of short selling activities focus on whether short sellers possess non-public information. Christophe, Ferri, and Angel (2004) find that pre-earnings announcement short-selling activities are significantly linked to post-announcement stock returns, and short sellers trade differently before earnings announcements and during other periods with little information-related events. Similarly, Safieddine and Wilhelm (1996) demonstrate a similar short selling pattern in the context of seasoned equity offerings, that increased short sales tradings precede low expected proceeds from new shares issuance. Boehmer, Huszar, and Jordan (2010) find that short selling interests can predict future stock returns. There is a consensus that short sellers have non-public information, and they incorporate such information into stock prices through trading.

It remains unsettled the debate of the effect of short selling restrictions on market quality. On the one hand, some studies find that short selling restrictions limit the ability of short sellers to trade information and thus support the removal of trading restrictions. Alexander and Peterson (2008) find that short sellers trade more aggressively and no market degradation after the uptick rule suspension. Saffi and Sigurdsson (2010) report that short selling constraints restrict price efficiency in a study of stocks across 26 countries. On the other hand, Kolasinki, Reed, and Thornock (2013) study the 2008 short selling ban and find that short selling restrictions improve the informativeness of short selling by screening out uninformed shorts. This paper contributes to this debate by analyzing the impact of the uptick rule suspension on the price discovery process.

III. Empirical strategy

The relation between information acquisition and trading efficiency is unclear. In the Grossman and Stiglitz (1980) model, improvements in trading mechanisms, such as lower transaction cost, looser restrictions and narrower bid-ask spread, can increase the information rent of the traders. The cost of incorporating information into the stock prices is lower and therefore encourages investors to gather non-public information. However, when the price is efficient, the potential gain of information trading diminishes and thus discourages information acquisition. To investigate this tension, I study the effects of the removal short selling price tests on information efficiency in the context of earnings announcements.

Pilot Program and Uptick Rule Suspension

The action of selling a security by an investor that does not own the security is called short selling. Compared to the purchase of securities, short selling is subject to various restrictions. To deliver the security to the buyer, the short-seller must first allocate someone who possesses the shares, then borrow the security and pay interest on the loan. The interest, also called borrowing fee, differs across stocks. Cohen, Diether, and Malloy (2007) show that the fee for an easy-to-borrow stock is around 0.05% per annum, while the fee for a hard-to-borrow stock can be as high as 10% per annum. Later, the short seller has to cover the short position by purchasing the security in the market and profit from declining market prices.

Besides the borrowing and covering requirements, in 1983 the SEC adopted Rule 10a-1, also known as the uptick rule, to restrict short selling in a declining market environment. The rule requires that ``a listed security may be sold (A) at a price above the price at which the immediately preceding sale was effected (plus tick), or (B) at the last sale price if it is higher than the last different price (zero-plus tick)."[6] On July 6, 2007, the SEC eliminated the uptick rule for all securities. Before the market-wide suspension of the uptick rule, the SEC established the Pilot Program (Reg SHO Rule 202T) on May 2, 2005. The Pilot Program is intended to determine the effectiveness of the uptick rule and the potential impacts of the rule elimination. Under the Pilot Program, about 1000 stocks (Pilot stocks) are chosen, and all short-selling prices tests are suspended for these stocks. The Pilot stocks include every third stock in the Russell 3000 index, ranked by volume, representing a broad cross-section of the stock market. The Pilot Program expired on August 6, 2007. Figure 1 shows the timeline of the short selling restriction rules.

Figure 1 about here

[6] Amendments to Exchange Act Rule 10a-1 and Rules 201 and 200(g) of Regulation SHO, https://www.sec.gov/divisions/marketreg/tmcompliance/rules10a-200g-201-secg.htm

The Pilot Program and the following market wide suspension of uptick rule provide an ideal setting for the difference-in-difference analysis of the impact of the uptick rule suspension on information acquisition. The two-stage nature of the change in regulation allows researchers to identify the effects of the uptick rule suspension, alleviating concerns of potential omitted variables. The analysis is conducted in the context of corporate quarterly earnings announcements, which have the greatest effect on stock price among all corporate events. Ball and Brown (1968) find that earnings announcements capture more than half of all the information about the firm, and market participants can capture most of the information before earnings announcements. Moreover, the earnings announcements are scheduled public events. This clarity facilitates the separation of pre-announcement price variation and post-announcement price reaction, which is essential for measuring information acquisition.

The difference-in-difference strategy allows researchers to explore the effect of the price test suspension on the information acquisition before the earning announcement. One can compare the effect of short selling price test elimination on the Pilot stocks (the treatment group) to the effect on non-Pilot stocks (the control group) when the Pilot Program takes place. We can also compare the different effects between the two groups when the uptick rule is later suspended for the non-Pilot stocks as well.

To further motivate the short-sale pilot, we provide direct evidence that information acquisition changed during the pilot.

Figure 2 about here

We observe the number of files downloaded from the SEC's EDGAR database around earnings announcements for each firm. We take the natural log of one plus the number of downloads as a direct measure of information acquisition, and plot the average of this variable for both pilot and control firms. We see an increase in downloads for pilot firms, but not control firms. It appears, therefore, that something changed with information acquisition during the pilot. We are unable to say if this increase in downloads is driven by information processors—these are public filings, so private information acquisition may not have changed—or if the increase in downloads is complementary to private information acquisition. To disentangle these two possibilities, we will need a different measure of information acquisition.

Regression Discontinuity Design

Regression discontinuity design is a quasi-experimental method used to study the change in effects around an artificial cutoff. Comparison of observations just above and below the cut-off alleviates concerns of identification. The artificial cut-off of the Russell 1000 index and the Russell 2000 index provides a setup to study how the suspension of the uptick rule affects firms with different institutional ownership levels.

The Russell 1000 and the Russell 2000 indexes track the top 1000 firms and the next 2000 largest firms ranked by market capitalization. The firms around the 1000 cut-off are similar, but there are more institutional funds tracking the biggest firms in the Russell 2000 index than the smallest ones in the Russell 1000 index due to the value-weighted nature of these two indexes. Chang, Hong, and Liskovich (2014) find that the index weight of the top Russell 2000 firms is about ten times the weight of the bottom Russell 1000 firms, while the total amounts of funds tracking each index are comparable. Consequently, index ownership and institutional ownership increases for the biggest firms in the Russell 2000 relative the smallest firms in the Russell 1000, as documented by Chang, Hong, and Liskovich (2014) and Crane, Michenaud, and Weston (2016), among others. Crane, Michenaud, and Weston (2016) note that the two-stage instrumental variable design of Chang, Hong, and Liskovich (2014) introduces noise and thus use actual membership in index rather than estimate the probability of membership. The noise is likely why Chang, Hong, and Liskovich (2014) do not find a statistically significant effect of index membership on institutional ownership, even though their point estimates are similar to Crane, Michenaud, and Weston (2016). We therefore view the design of Chang, Hong, and Liskovich (2014) as more conservative, and so follow them.

We limit our sample to 2007 because Russell changed their policy toward reconstitutions. In particular, the transition from one index to another only occurs if there is a more substantial change in size (citation needed). This policy change limits the usefulness of our discontinuity design.

IV. Data and variable construction

This paper relies on four primary sources of data for the empirical analyses: the Center for Research in Securities Prices (CRSP); the Thomson Reuters Institutional Brokers' Estimate System (I/B/E/S); Ken French's data library[7]; and the Thomson Reuters Filing 13F. CRSP provides historical daily stock returns around earnings announcements, market capitalization, and book-to-market value. I/B/E/S provides quarterly earnings announcements dates, reported earnings per share (EPS), and analysts' mean estimate of EPS. Thomson Reuters Filing 13F provides the institutional holdings of the firms' shares. Ken French data library facilitates the factor returns needed to compute the cumulative abnormal returns of the stocks. The list of Pilot stocks is available on the SEC website[8].

The empirical analysis includes all stocks with the price greater than $5 in the Russell 3000 index and their quarterly earnings announcements between January 1, 2002, and December 31, 2007. The list of stocks is updated annually. When stocks are removed from the Russell 3000 index, they are excluded from the analysis. Similarly, when firms are introduced into the index, their stocks are included in the analysis.

Moreover, the core analysis focuses on earnings announcements with significant earnings surprises, as in Weller (2017). Traders' private information regarding these big surprises, if they possess any, is more material. Traders are more likely to trade on such information and benefit from it before the earnings announcements. The measures of information acquisition are more precise in this context as well. Further, if there is no information acquirable, then short sellers will not matter one way or another. For this reason,

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data

[8] https://www.sec.gov/spotlight/shopilot/currentpilota41305.txt

our difference-in-difference analysis drops neutral announcements as well as the smallest 25% of both good and bad announcements.

Measure of information acquisition

To capture the pre-announcement information acquisition, we construct a similar measure to the (II) measure proposed by Jiang, Shen, Wermers and Yao (2017). The I*nformation Intensity* is the ratio of post-announcement realized variance to total realized variance during the whole earnings announcement period, which includes both the pre- and post-announcement period. Pre-announcement period is the 22 trading days before the quarterly earnings announcements date, and the post-announcement period is two trading days after the announcement data. The two trading day period is selected to allow for post-announcement drift. For stock *i* and earning announcement *t*, the information intensity is defined as:

$$II_{i,t} = \frac{RV_{i,t}^{T-1,T+2}}{RV_{i,t}^{T-22,T+2}}$$

The realized variance $RV_{i,t}^{t_1,t_2}$ is the sum of daily squared returns from t_1 to t_2.

The information intensity measure captures the proportion of information not incorporated into the stock price before the earning announcement to the total amount of information related to the announcement. Aggressive informed trading before corporate earnings announcements help incorporate information into the stock prices and thus lower the information intensity towards zero. With sparse informed trading, the pre-announcement stock price becomes less informative, most information is released after the public announcements, and the information intensity ratio increases towards one. A higher value of information intensity represents less efficient pre-announcement information acquisition. Figure 2 plots this measure over time and for both the control and treated samples.

Figure 3 about here

We see an interesting time trend in information intensity. Starting from 2002 thru the end of our sample, we notice a 50% increase in the contribution of earnings to variance. This trend is identical for both pilot stocks and control stocks. There could be a variety of reasons for the trend. One possibility is that earnings announcements could be more informative. Another possibility is that trading has become increasingly deregulated with the reductions in tick sizes and eventual removal of short sale constraints—more efficient trading allows traders to capture rents that could have otherwise gone to acquirers of fundamental information, who therefore drop out of the market. A third possibility is that the increase in indexing and passive ownership of stocks reduces the number of active managers who perform fundamental analysis. To tease out the particular drivers of the trend we need quasi-natural experiments.

Before the implementation of the Pilot Program in 2005, the averages of intensity are similar for the two groups of stocks. During the Pilot program, from 2005 to 2007, the mean information intensity for the Pilot stocks increases relative the control stocks. After the market-wide suspension of the uptick rule in 2007, the two time-series converges, and the levels are higher than the pre-Pilot Program period. These time-series trends set the basis for the difference-in-difference analysis in the next section.

Other variables

The implementation of difference-in-difference analysis requires several dummy variables to distinguish the treatment group and the control group, and the different phases of the uptick rule suspension. *Pilot company* is a dummy variable that equals to 1 for companies in the Pilot Program, and 0 for the non-Pilot stocks. *Pilot period* indicates the period when the uptick rule suspension is only applied to the Pilot stocks. This dummy variable equals 1 for observations between May 2, 2005, and July 6, 2007, and 0 otherwise. *Post period* indicates the period when the uptick rule is suspended for all stocks. This dummy variable equals 1 for observations later than July 6, 2007, and 0 otherwise. Dummy variable *No Restriction* is an indicator for observations that are exempt from short selling price test, either through the Pilot Program or the market wide uptick rule suspension. *No Restriction* is therefore our key difference-in-difference variable

To reduce the noise of neutral news, the analysis excludes the announcements with close to zero earnings surprises. More specifically, *Earnings Surprise* is defined as the difference between the reported and the analysts estimated earnings per share scaled by the lag price of shares at the beginning of the announcement period. The empirical analyses exclude the lower (higher) 25% of observations with positive (negative) earnings surprises and the earnings announcements with zero earnings surprises. The remaining observations contain more significant earnings surprises. The cutoff does not affect the results.

To improve statistical power, we include the following control variables in the analysis: market capitalization and equity book-to-market value. In certain analyses, we will study changes in institutional ownership. *Institutional ownership* is the ratio of the number of shares of the firm held by institutions at the end of the quarter to the total amount of shares outstanding.

Insert table 1 about here

Table 1 reports the summary statistics of the main information acquisition measures and the control variables. The summary shows that the empirical analysis includes a broad cross-section of the stock market. The mean and median of the *Information intensity* is around 0.27, which suggests that on average about 73% of the earnings-related information is priced before the earnings announcements. Earnings announcements are also fairly volatile, with a median standard deviation of 11% over the month, and 4.5% in the days immediately following an earnings announcement.

Table 2 shows that the Pilot stocks have similar characteristics to the non-Pilot stocks before the initiation of the Pilot Program. Column (1) and (2) report the mean of the main variables of the Pilot stocks and the non-Pilot stocks before the announcement of the list of pilot stocks. Column (3) reports the difference of the mean between the two groups, and column (4) reports the t-statistics for the mean difference t-tests. All t-statistics are not economically or statistically significant, assuring the randomness of the Pilot Program, a necessary condition for the validity of the difference-in-difference analysis.

Insert table 2 about here

V. Does short-selling deter earnings-related information acquisition?

The main empirical analysis focuses on the change in information acquisition before the quarterly earnings announcements during the uptick rule suspension. The below equation represents the difference-in-difference regression relating *Information intensity* to the change of short selling restrictions:

$$II_{i,t} = \beta_1 PilotCompany_i + \beta_2 NoRestriction_{i,t} + \beta_3 Controls_{i,t} + \gamma_t + \epsilon_{i,t}$$

Where *PilotCompany* is a dummy variable that equals to one for firms chosen in the Pilot Program, and zero otherwise; *NoRestriction* is a dummy variable that equals to one for observations that are exempt from short selling price tests, and zero otherwise; γ_t are the quarterly fixed effects. Standard errors are clustered by firm and by quarter to allow residuals to be correlated within firm and within the same quarter. Controls include the natural logarithm of market capitalization as well as the stock's book-to-market.

Column (1) of Table 3 presents the result of our main regression specification. The estimated coefficients suggest that the uptick rule suspension increases information intensity by 1.5 p.p., while the mean and the median of information intensity are 0.271 and 0.207, respectively. In other words, there is about a 5.5-7.5% loss in the portion of earnings-related information acquired prior to the earnings announcements when short sales are easier. This loss in efficiency is both statistically and economically significant.

Table 3 about here

Column (2) breaks the difference-in-difference coefficient *NoRestriction* into its two components. Treated observations are a) pilot stocks during the pilot program, and b) all stocks after the pilot program. By replacing *NoRestriction* with the interaction of *PilotCompany* and these two time periods, we can study the reversal in the post-pilot period where the control stocks are given the treatment. The coefficient on *PilotComp*PilotPeriod*—the effect of the pilot program on pilot securities—is 0.014, which is nearly identical to our main coefficient in column (1). The coefficient on *PilotComp*PostPeriod* measures the relative response of the control stocks once the uptick rule is removed for them—we see that the control stocks exhibit higher *Information Intensity* relative the pilot stocks after they are subject to more short selling.

Column (3) explores the symmetry of the effect by including an interaction for *BadNews*. If our main results are being driven by the direct actions of short-sellers, then we should see an asymmetry between good news and bad news as the uptick rule makes trading on bad news particularly difficult. To measure this, we interact our difference-in-difference variable with *BadNews*. *NoRestriction*BadNews* measures the incremental effect of bad news on top of the average effect for both good and bad news. The coefficient on this interaction is statistically insignificant, while the coefficient on *NoRestriction* is little changed from column (1). The symmetry is consistent with a reduction of information acquisition, where the acquirer does not know ex-ante whether the information will be good or bad; the symmetry is inconsistent with the direct actions of short-sellers driving our results—eg through a reduction in post-earnings announcement drift (Reed (2007)).

The dynamics of volatility are also illuminating. Figure 4 plots the share of volatility of each day during the month around earnings announcements, and does so separately for firms subject to the uptick rule and those not bound by it.

Insert figure 4 about here

Panel A shows the contribution of each day to realized variance for the entire sample. We see that firms that are not subject to the uptick rule demonstrate substantially more volatility on the day of announcement and the following day. This extra volatility is pulled from the first twenty days of the month. But we know from figure 2 that there is a time trend in information intensity, so the increase in information intensity during and after the pilot program may be an artefact of the program occurring later in the sample.

To address the time trend, for each trading day -22 to 2 we calculate the average share of volatility for all earnings announcements in a given quarter. Then we demean each individual stock-quarter-trading-day by the average for the quarter-trading-day. We finally plot the residual for both pilot and control firms during the pilot period. The results are shown in panel B. We see a marked increase in the share of volatility that occurs on the day of the announcement for pilot stocks. The higher share at announcement is pulled from days -5 to -3, as well as some from days 1-2. Pulling volatility from days -5 to -3 is consistent with a reduction in information being priced prior to the announcement and hence lower information acquisition; pulling volatility from days 1-2 is consistent with a reduction in post-earnings announcement drift as a result of short-selling. These two facts are consistent with the efficient pricing by short-sellers deterring information acquisition before the public announcement.

VI. Does information intensity reflect the information content of earnings surprises?

It is still possible that short-sellers cause a (symmetric) increase in the information content of earnings announcements. If earnings are more relevant when short-selling is easier, then we should expect to see a greater share of volatility coming from announcement. We try to rule out this alternative by showing that key quantities do not change for our treatment group. Table 4 presents balancing tests, which run our difference-in-difference regression with different dependent variables than *Information Intensity*.

Table 4 about here

Column 1 reports the effect of short-selling on realized variance at announcement, while column 2 reports the difference-in-difference analysis for realized variance over the month. In neither case is there an increase in variance, which seems inconsistent with more fundamental information being contained in the earnings announcement as opposed to a greater share of the information being priced at announcement. Column (6) looks at the probability of an earnings surprise, which is important given that our baseline results condition on an earnings surprise. It could be, for example, that short sellers help analysts make better forecasts and thereby improve information acquisition on a margin that we do not see. The coefficient on column (6), however, is statistically and economically insignificant—over 60% of our earnings are classified as surprises, while short-selling reduces the probability by 0.3 p.p. We do not rule out, however, that short-selling improves the information content of earnings for the 40% of neutral or mild surprises (Fang, Huang, and Karpoff (2016)).

The coefficients in table 4 for market capitalization and book-to-market are likewise insignificant. We do see an increase in institutional ownership as a result of the pilot program. It is possible that this is one mechanism through which the program works—more demand for shorting in the pilot stocks leads to an endogenous increase in institutional ownership, which leads to a change in information acquisition. We will explore this possibility in more depth when we study mechanisms.

Table 5 measures the effect of the pilot program on trading volume. It has been documented that the pilot program lead to an increase in shorting volume, which we confirm. Volume increased both around the announcement as well as over the entire month.

Insert table 5 about here

The fraction of volume that occurs after announcement, however, is unchanged when shorting is easier. This again seems inconsistent with firms releasing more information or different types of information when short-selling is easier. If earnings surprises are substantially harder to interpret for pilot firms, we may expect a greater fraction of the volume to occur at announcement. The constant fraction of volume does not cleanly rule out changes in the information content of earnings, but at least it does not present a red flag that something else changed concurrent with the pilot.

Finally, we present our results for the entire sample of earnings announcements, split by quintile of earnings surprise. Table 6 shows the difference-in-difference results for each group:

Insert table 6 about here

We obviously lose statistical power by splitting the sample into five parts. However, the point estimate always points in the same direction and ranges from 0.006 to 0.014. This consistency provides evidence that short-sellers deter information acquisition across the board. If our results are driven by a direct consequence of shorting at announcement, or if announcements are managed on account of short sellers, we should expect a wider dispersion of coefficients across good and bad news.

VII. When does the uptick rule bind? When does it affect information acquisition?

We have found little evidence that our results on information acquisition are driven by a change in reporting strategy on account of short-sellers. The fundamental information does not appear to change; rather, the information is disproportionately priced at the announcement. We next study the differential effects of the uptick rule. First, the uptick rule may not bind for all stocks. Second, the effect of the uptick rule on information acquisition can vary across stocks. On average, the uptick rule deters fundamental analysis, but it is possible that the uptick rule encourages information acquisition by short sellers more for some stocks.

Changes in institutional ownership as an indication of relaxed constraints

When the uptick rule is repealed, the cost of short-selling goes down. This translates into a shift in the demand curve for borrowed shares, assuming the uptick rule was previously binding. When the demand curve shifts out, the new equilibrium will be higher on the supply curve. If institutional ownership is a good proxy for the supply of shares, then we should see an increase in institutional ownership where the uptick rule is relaxed.[9]

Table 7 runs our difference-in-difference specification for different terciles of market capitalization with institutional ownership as the dependent variable.

Insert table 7 about here

We see evidence that institutional ownership increases by 1.9 – 2.8 p.p. for the bottom two terciles, while the coefficient for the top tercile is very close to zero. If large stocks are relatively liquid, then the uptick rule may not have been binding. Likewise, for large stocks with liquid option markets, traders could form synthetic short positions to effectively circumvent the uptick rule.

Table 8 runs our difference-in-difference specification for different terciles of market capitalization with information intensity as the dependent variable.

[9] This is not a necessary condition to show that the uptick rule was binding. It is possible that the supply curve also shifts inward when the uptick rule is relaxed (e.g. institutions choose to not hold shares that may face price declines), in which case the effect on institutional ownership is ambiguous. Regardless, a change in institutional ownership can signify a relaxation in the constraint.

Insert table 8 about here

Consistent with table 7, we see no increase in information intensity for large stocks during the pilot program. If the uptick rule did not bind to begin with, then its relaxation should not affect information acquisition. Our baseline results are entirely driven by the middle tercile where the coefficient is nearly three times as large as the baseline in table 3. Further, the middle tercile is statistically different from the others.

While table 7 implies that the uptick rule constrained small stocks, table 8 shows no effect on information acquisition. It seems likely that information asymmetries are too large for these stocks, such that trading is likely to be inefficient whether or not the uptick rule is in place, so the incentives to acquire information are not affected by the uptick rule. Alternatively, it could be that the direct of effect of improved trading on information acquisition exactly offsets the indirect deterrent effect from an increase in sophisticated short sellers.

Russell reconstitution

The uptick rule is not the only constraint facing short sellers—they must also find shares to borrow. If short-selling deters information acquisition, then we should see a particularly large effect when both constraints are simultaneously relaxed.

The change in institutional ownership toward pilot stocks in table 7 underscores the importance of institutional ownership for short selling. It also highlights the endogeneity of institutional ownership, which complicates interpretation. To find a particularly relevant shock to the uptick rule, therefore, we also need a shock to institutional ownership—these are both constraints to short-selling which interact with each other.

Serendipitously, the SEC's pilot program easily accommodates such a shock at the threshold separating the Russell 1000 and Russell 2000. As has been documented in a variety of studies (e.g. Chang, Hong, and Liskovich (2014) and Crane, Michenaud, and Weston (2016)) the index weights for the biggest stocks in the Russell 2000 are substantially higher than the weights for the smallest stocks in the Russell

1000, creating a discontinuity in institutional ownership despite otherwise similar appearances. We therefore combine Chang, Hong, and Liskovich's (2014) empirical design with the pilot program. In particular, we separately estimate the below two-stage instrumental variable model for both pilot and control stocks. Our first-stage is:

$$\mathrm{R1000}_{i,t} = \alpha + b_1(\mathrm{Rank}_{i,t} - c_t) + b_2\tau_{i,t} + b_3\tau_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + e_{i,t}$$

We estimate the first stage once per Russell year, where the Russell years run from June to May and correspond to annual reconstitutions of the indices. $\tau_{i,t}$ is the key excluded instrument—it is an indicator equal to one for securities that are ranked in the top 1000 by size, where size is measured at the last trading day in May. Being in the top 1000 stocks discontinuously increases the probability of being in the Russell 1000, which typically corresponds to a drop in institutional ownership.

We apply the first stage to quarterly data in the second-stage for two variables—institutional ownership and information intensity:

$$\mathrm{IO}_{i,t}^{avg} = \alpha + \beta_1(\mathrm{Rank}_{i,t} - c_t) + \beta_2\mathrm{R}\widehat{1000}_{i,t} + \beta_3\mathrm{R}\widehat{1000}_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + \epsilon_{i,t}$$

$$\mathrm{II}_{i,t}^{avg} = \alpha + \beta_1(\mathrm{Rank}_{i,t} - c_t) + \beta_2\mathrm{R}\widehat{1000}_{i,t} + \beta_3\mathrm{R}\widehat{1000}_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + \epsilon_{i,t}$$

Table 9 reports the first-stage results. Our coefficients are broadly in line with Chang, Hong, and Liskovich (2014). Upon crossing the threshold for the 1000th largest stock, the probability of inclusion in the Russell 1000 increases by over 80 p.p., with the r-squared above 90 p.p.

Table 9 about here

Table 10 reports the second-stage results for institutional ownership, and figure 5 plots the reduced form relationship.

Table 10 about here

Figure 5 about here

Consistent with Chang, Hong, and Liskovich (2014), the control stocks in panel B of table 10 exhibit a statistically insignificant drop in institutional ownership of 4.5-5.5 p.p. upon inclusion in the Russell 1000 index. The pilot stocks, strikingly, exhibit the opposite pattern—they see an increase in institutional ownership of around 11 p.p.. The effect for pilot stocks is marginally significant for smaller bandwidths, but the coefficient is stable for a wide range of bandwidths. Institutions appear to strategically avoid pilot stocks when the institution is forced to rebalance at reconstitution. The repeal of the uptick rule therefore shocked not only the demand for lendable shares, but also the supply curve. This shock to the supply curve lets us study the interaction of two constraints on short-selling: the uptick rule and the supply of shares.

Table 11 reports the second-stage results for information intensity, and figure 6 plots the reduced form fit.

Table 11 about here

Figure 6 about here

We see an increase in information intensity for pilot stocks in the Russell 1000, which corresponds to higher institutional ownership in table 10. This is consistent with a very strong interaction between the uptick rule and the supply of lendable shares—information acquisition falls almost three times more than the sample average when institutional ownership is simultaneously shocked with the removal of the uptick rule. The result is robust to a range of bandwidths.

Panel B duplicates the analysis for control stocks. At the discontinuity, control stocks face a marginal drop in institutional ownership but no relaxation of the uptick rule. We see statistically insignificant effects on *information intensity* for the control stocks. Thus, the effect of institutional ownership on deterring information acquisition only seems to matter when it is combined with easier short-selling.

Finally, table 12 replicates the RD analysis for the placebo period of 2002-2004.

Table 12 about here

We find no statistically discernable effect of index membership on information acquisition for either the pilot or control firms. If anything, the point estimates suggest that institutional ownership by itself helps information acquisition—the coefficient on R1000 is positive, implying a greater contribution of earnings to variance for stocks with lower institutional ownership—consistent with Boone and White (2015).

VIII. Conclusion

The relation between the two components of price discovery, information acquisition and incorporation of existing information into security prices, remains unclear in the literature. This paper shows a situation where improvements in trading mechanism negatively affect information acquisition. More specifically, the suspension of the uptick rule enhances the trading of available information, but it deters the amount of information gathered by traders at the first place.

More specifically, the empirical analyses show that the suspension of short selling price tests decreases the portion of pre-earnings announcements information to the total amount of earnings-related information. Moreover, the magnitude of the loss in information efficiency varies cross-sectionally. Firms with higher institutional ownership suffer from larger losses in pre-announcement information. The removal of the uptick rule makes short sales of firms with high institutional ownership efficient, while short sales of firms with low institutional ownership remain restricted due to other shorting constraints, such as high borrowing fees and scarce share supply.

These findings pose a challenge for financial market regulators and question the benefits of financial innovations that are intended to facilitate trading. Reducing trading restrictions, which seemingly facilitates the incorporation of information into security price through active trading, can discourage investors from gathering new information, and thus reduces the total amount of information to be priced. As a result, the price discovery process in the financial market worsens. Thus, it is worth investigating further to what extent relaxing market restrictions is beneficial and what kind of market regulation should be imposed.

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Figure 1: Short selling restriction timeline

This figure plots the history of short-selling restrictions used in this paper.

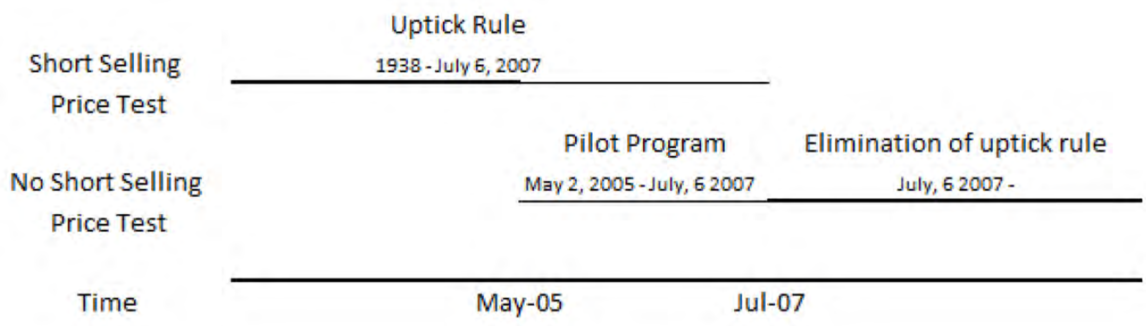


Figure 2: Direct information acquisition from SEC's EDGAR

Using the server logs from the SEC's EDGAR database, we track the number of downloads for each company around its earnings announcements. For each quarter, we calculate $\ln(1 + Number\ of\ Downloads)$ for every firm and plot the average separately for both pilot and control firms. We start in 2004 as the database was not widely used before then. The axis also has a break from the end of 2005 to the middle of 2006 on account of corrupted files on the server.

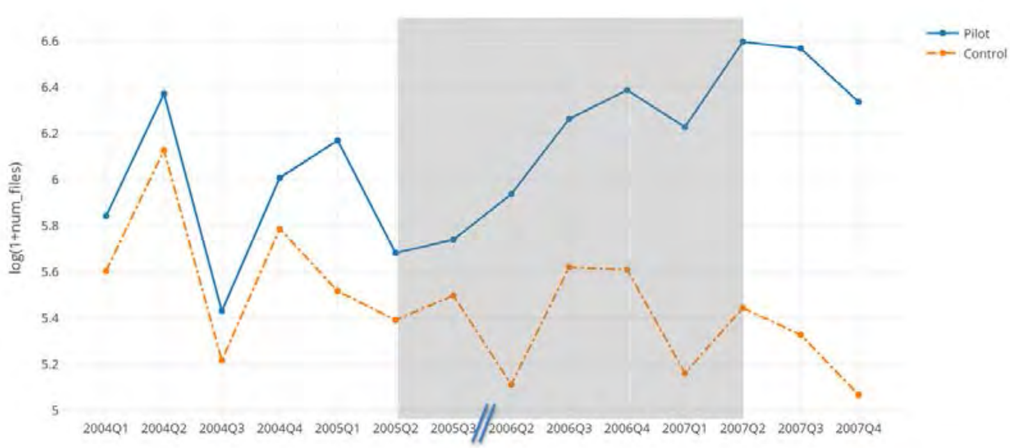


Figure 3: Time trend of information intensity measure

This figure plots our measure of information intensity over time. For firm *i* and quarterly earnings announcement *t*, the information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. We separately plot his measure for firms in the pilot group as well as the rest of the Russell 3000. Shaded quarters signify the pilot program.

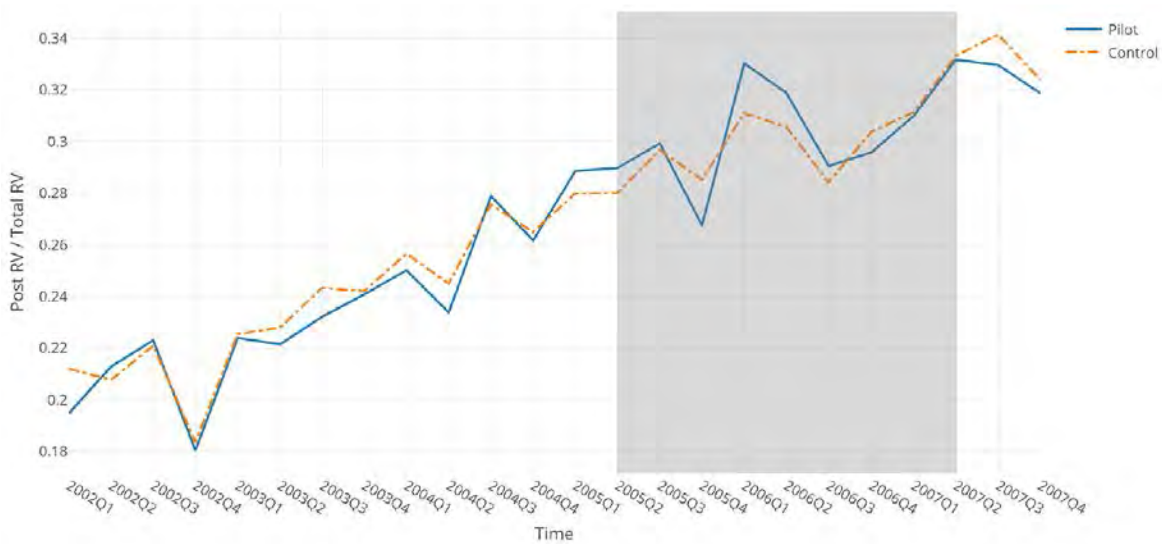
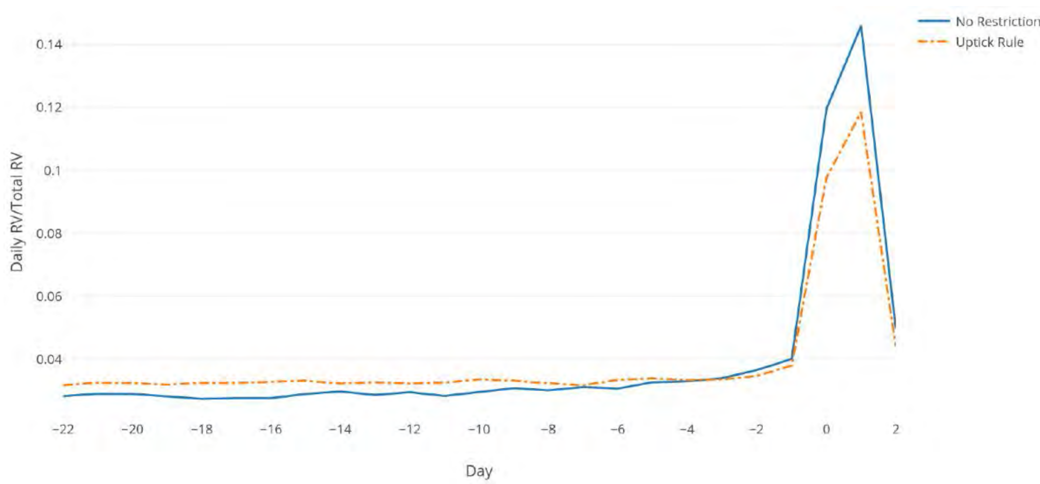


Figure 4: Dynamics- contribution of each day's RV to total RV

This figure plots the contribution of each day's squared return to the total realized variance in the month around an earnings announcement. The total realized variance is the sum of squared returns from 22 days before announcement to 2 days after. Each day's contribution is the squared return on that day. Panel A plots the average day's contribution separately for stock-quarters that are not bound by the uptick rule (*NoRestriction*) and stock-quarters that are subject to the uptick rule. For Panel B, we first absorb the average contribution of each trading day in each quarter during the pilot program. Then we plot the residual for stock-quarters that are bound by the uptick rule and those that are not.

Panel A: Unconditional



Panel B: After absorbing quarterly averages for each day during the pilot program

Figure 5: Reduced form RD for institutional ownership

This figure plots the reduced form relationship between institutional ownership and a firm's expected constituency in the Russell 1000 for both the pilot and control stocks during the pilot program. We follow Chang, Hong, and Liskovich (2014) and fit the following equation for both groups of stocks:

$$\mathrm{IO}_{i,t} = \alpha + \beta_1(\mathrm{Rank}_{i,t} - c_t) + \beta_2\tau_{i,t} + \beta_3\tau_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + \epsilon_{i,t}$$

For each Russell year t, $\mathrm{IO}_{i,t}$ is the average institutional ownership level for firm i. $Rank_{i,t}$ is the firm's rank based on its market capitalization on the last trading day of May, in ascending order. c_t is the cutoff rank of the Russell 1000 index and the Russell 2000 index. $\tau_{i,t}$ is the omitted instrument and equals one for firms with rank greater than the cutoff c_t, and zero otherwise. We use a bandwidth of 220; every point represents the average over five ranks. Observations with prices less than \$5 at the beginning of the period are dropped.

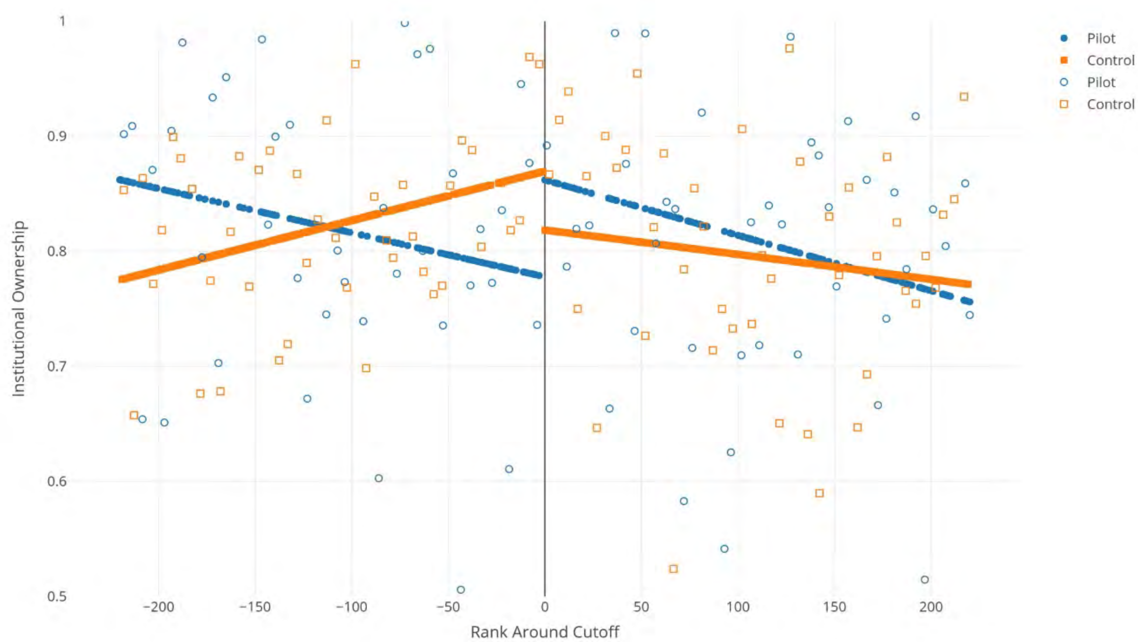


Figure 6: Reduced form RD for information intensity

This figure plots the reduced form relationship between information intensity and a firm's expected constituency in the Russell 1000 for both the pilot and control stocks during the pilot program. We follow Chang, Hong, and Liskovich (2014) and fit the following equation for both groups of stocks:

$$\mathrm{II}_{\mathrm{i,t}}^{\mathrm{avg}} = \alpha + \beta_1(\mathrm{Rank}_{\mathrm{i,t}} - \mathrm{c_t}) + \beta_2\tau_{\mathrm{i,t}} + \beta_3\tau_{\mathrm{i,t}} * (\mathrm{Rank}_{\mathrm{i,t}} - \mathrm{c_t}) + \epsilon_{\mathrm{i,t}}$$

For each Russell year t, $\mathrm{II}_{\mathrm{i,t}}^{\mathrm{avg}}$ is the average information intensity measure for firm i. The information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. $Rank_{i,t}$ is the firm's rank based on its market capitalization on the last trading day of May, in ascending order. c_t is the cutoff rank of the Russell 1000 index and the Russell 2000 index. $\tau_{i,t}$ is the omitted instrument and equals one for firms with rank greater than the cutoff c_t, and zero otherwise. We use a bandwidth of 220; every point represents the average over five ranks. Observations with prices less than $5 at the beginning of the period are dropped.

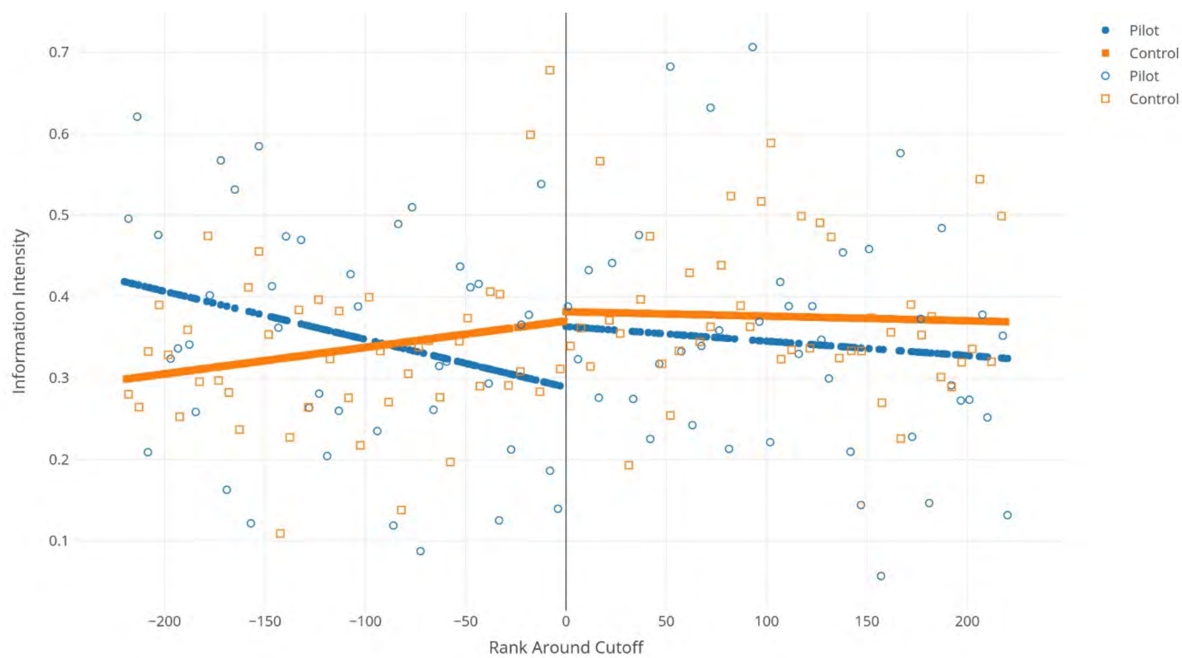


Table 1: Key Variables Summary Statistics

This table reports summary statistics of the information acquisition measure and firm characteristics. For firm *i* and quarterly earnings announcement *t*, the information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. The firm characteristics include log of market capitalization, equity book-to-market, and institutional ownership. Observations with prices less than $5 at the beginning of the period are dropped.

Statistic	$RV^{T-1,T+2}/RV^{T-22,T+2}$	$RV^{T-1,T+2}$	$RV^{T-22,T+2}$	Log(Market Cap.)	Book-to-Market	Inst. Ownership
N	54,323	54,323	54,323	50,447	50,447	54,323
Mean	0.271	0.007	0.024	7.175	0.460	0.702
St. Dev.	0.224	0.021	0.049	1.454	0.370	0.255
Pctl(25)	0.092	0.001	0.006	6.102	0.265	0.540
Median	0.207	0.002	0.012	6.940	0.419	0.736
Pctl(75)	0.403	0.006	0.025	7.989	0.600	0.884

Table 2: Pilot and Non-Pilot Firm Characteristics

Column (1) and (2) report the mean values of the main variables of the Pilot firms and the non-Pilot firms, respectively, right before the announcement of the list of Pilot stocks. Column (3) reports the difference of the mean between the two groups, and column (4) reports the t-statistics for the mean difference t-tests.

Characteristics	Pilot Firms Mean (1)	Non-Pilot Firms Mean (2)	Difference (3)	T-Statistics (4)
$\frac{RV_{i,t}^{T-1,T+2}}{RV_{i,t}^{T-22,T+2}}$	0.235	0.245	-0.010	-1.134
Market. Cap	7.243	7.179	0.064	1.007
Book-to-Market	0.423	0.420	0.003	0.287
Instit. Ownership	0.703	0.690	0.013	1.272
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3: Impact of the Uptick Rule Suspension

This table reports the difference-in-difference analysis of the suspension of the uptick rule. For firm *i* and quarterly earnings announcement *t*, the information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2} / RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. *Pilot Company* is a dummy variable that equals 1 for companies in the pilot program. *Pilot Period* and *Post Period* are indicators for observations between May 2, 2005 and July 6, 2007, and after July 6, 2007, respectively. *No Restriction* is the difference-in-difference variable—an indicator equal to one for observations that are exempt from the uptick rule. *Bad News* is a dummy variable equal to 1 for observations with reported EPS lower than analysts' estimate. The control variables include market capitalization and equity book-to-market. We exclude observations with neutral earnings announcements, which are defined as the top (bottom) 25% of observations with negative (positive) earnings surprises. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter and are reported in parentheses.

	Dependent variable:		
	Information Intensity		
	(1)	(2)	(3)
Pilot Comp.	−0.008	−0.006	−0.008
	(0.005)	(0.005)	(0.005)
No Restriction	0.015**		0.012*
	(0.006)		(0.006)
Bad News			−0.002
			(0.005)
Pilot Comp.×Pilot Period		0.014**	
		(0.007)	
Pilot Comp.×Post Period		−0.011**	
		(0.005)	
Pilot Comp.×Bad News			−0.0001
			(0.009)
Bad News×Pilot Period			−0.016
			(0.011)
Bad News×Post Period			0.005
			(0.020)
Bad News×No Restriction			0.010
			(0.017)
log(Market Cap.)	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)
Book-to-Market	−0.008*	−0.008*	−0.008*
	(0.005)	(0.005)	(0.005)
Quarter FEs	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	32,157	32,157	32,157
R^2	0.615	0.615	0.615

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Balancing Tests

This table reports balancing tests for the difference-in-difference model. Column (1) and (2) show the balancing tests of the numerator ($RV_{i,t}^{T-1,T+2}$) and denominator ($RV_{i,t}^{T-22,T+2}$) of the information intensity measure. Columns (3) – (5) report the balancing test for the control variables: market capitalization, equity book-to-market, and institutional ownership. Columns (1) – (5) exclude observations with neutral earnings announcements, which are defined as the top (bottom) 25% of observations with negative (positive) earnings surprises. Column (6) reports the results for an *Earnings Surprise Dummy*, which is equal to 1 if the earnings announcement is not neutral, and 0 if the announcement is neutral. *Pilot Company* is a dummy variable that equals 1 for companies in the pilot program. *No Restriction* is the difference-in-difference variable—an indicator equal to one for observations that are exempt from the uptick rule. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter and are reported in parentheses.

	Dependent variable:					
	$RV_{i,t}^{T-1,T+2}$	$RV_{i,t}^{T-22,T+2}$	Log Market Cap.	Book-to-market	Inst. Ownership	Earnings Surprises Dummy
	(1)	(2)	(3)	(4)	(5)	(6)
Pilot Comp.	-0.001^{*}	-0.002^{*}	0.198^{***}	0.017	0.015	0.003
	(0.0004)	(0.001)	(0.062)	(0.013)	(0.010)	(0.007)
No Restriction	0.001	0.002	0.071	0.015	0.016^{**}	-0.003
	(0.001)	(0.001)	(0.049)	(0.011)	(0.007)	(0.007)
log(Market Cap.)	-0.002^{***}	-0.005^{***}		-0.045^{***}	0.032^{***}	-0.004
	(0.0002)	(0.001)		(0.006)	(0.003)	(0.003)
Book-to-Market	-0.001^{**}	-0.005^{***}	-0.487^{***}		0.025^{***}	0.014^{**}
	(0.001)	(0.002)	(0.176)		(0.010)	(0.007)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	32,157	32,157	32,157	32,157	32,157	50,447
R^2	0.135	0.267	0.965	0.595	0.892	0.855

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5: Trading volume

This table reports the difference-in-difference analysis of the suspension of the uptick rule. For firm *i* and quarterly earnings announcement *t*, we measure dollar volume for certain intervals of days. The first column measures volume in the two days after the announcement, while the second column also includes the month before announcement. Column three takes the ratio of the first two measures. *Pilot Company* is a dummy variable that equals 1 for companies in the pilot program. *No Restriction* is the difference-in-difference variable—an indicator equal to one for observations that are exempt from the uptick rule. The control variables include market capitalization and equity book-to-market. We exclude observations with neutral earnings announcements, which are defined as the top (bottom) 25% of observations with negative (positive) earnings surprises. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter and are reported in parentheses.

	Dependent variable:		
	$Volume_{i,t}^{T-1,T+2}$	$Volume_{i,t}^{T-22,T+2}$	$\frac{Volume_{i,t}^{T-1,T+2}}{Volume_{i,t}^{T-22,T+2}}$
Pilot Comp.	−273,561.600	−1,742,356.000	−0.002
	(474,766.200)	(3,593,961.000)	(0.002)
No Restriction	536,945.400***	2,655,294.000**	0.003
	(174,120.000)	(1,175,487.000)	(0.002)
log(Market Cap.)	3,533,881.000***	28,860,484.000***	−0.005***
	(437,451.400)	(3,293,821.000)	(0.001)
Book-to-Market	112,920.700	2,491,420.000	−0.006***
	(283,098.100)	(2,450,697.000)	(0.002)
Quarter FEs	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	32,160	32,160	32,160
R^2	0.225	0.275	0.754
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Sub-sample by size of earnings surprise

This table studies the effect of the uptick rule on information intensity for different subsamples of earnings surprises. At the end of each quarter *t*, five portfolios are formed by ranked value of earnings surprises, defined as the difference between the announced EPS and the analysts' mean estimate of EPS, with the surprise scaled by the share price at the start of the announcement period. For firm *i* and quarterly earnings announcement *t*, the information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. Column (1) includes observations in the lowest quintile of earnings surprises, while column (5) contains observations in the highest quintile of earnings surprises. *Pilot Company* is a dummy variable that equals 1 for companies in the pilot program. *No Restriction* is the difference-in-difference variable—an indicator equal to one for observations that are exempt from the uptick rule. The control variables include market capitalization and equity book-to-market. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter and are reported in parentheses.

	$RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$				
	Sub Sample: Earnings Surprises				
	Bad		Neutral		Good
	(1)	(2)	(3)	(4)	(5)
Pilot Comp.	−0.007	−0.003	−0.001	−0.006	−0.012**
	(0.009)	(0.007)	(0.005)	(0.006)	(0.005)
No Restriction	0.016	0.005	0.006	0.015	0.011
	(0.014)	(0.011)	(0.011)	(0.011)	(0.008)
log(Market Cap.)	−0.004	0.003*	−0.0001	0.002	0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Book-to-Market	0.011*	−0.052***	−0.078***	−0.055***	−0.006
	(0.006)	(0.011)	(0.016)	(0.011)	(0.007)
Quarter FEs	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	9,918	11,215	9,182	10,178	9,936
R^2	0.588	0.602	0.628	0.629	0.632
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Institutional ownership by market capitalization

This table studies the effect of the uptick rule on institutional ownership for different subsamples of market capitalization. At the end of each quarter *t,* three portfolios are formed by ranked value of market capitalization. For firm *i* and quarterly earnings announcement *t*, the institutional ownership is calculated as the fraction of shares outstanding that are owned by institutions. Column (1) includes observations in the lowest tercile of size, while column (3) contains observations in the highest tercile of size. *Pilot Company* is a dummy variable that equals 1 for companies in the pilot program. *No Restriction* is the difference-in-difference variable—an indicator equal to one for observations that are exempt from the uptick rule. The control variables include market capitalization and equity book-to-market. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter and are reported in parentheses.

	Institutional Ownership		
	Sub Sample: Size		
	Small	Medium	Large
	(1)	(2)	(3)
Pilot Comp.	0.023	0.013	−0.011
	(0.017)	(0.015)	(0.014)
No Restriction	0.028*	0.019*	0.004
	(0.015)	(0.011)	(0.009)
log(Market Cap.)	0.101***	0.039**	−0.021***
	(0.016)	(0.016)	(0.005)
Book-to-Market	0.102***	0.062***	−0.094***
	(0.016)	(0.020)	(0.021)
Quarter FEs	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	10,593	10,603	10,937
R^2	0.856	0.898	0.929

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Information intensity by market capitalization

This table studies the effect of the uptick rule on information intensity for different subsamples of market capitalization. At the end of each quarter *t*, three portfolios are formed by ranked value of market capitalization. For firm *i* and quarterly earnings announcement *t*, the information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. Column (1) includes observations in the lowest tercile of size, while column (3) contains observations in the highest tercile of size. *Pilot Company* is a dummy variable that equals 1 for companies in the pilot program. *No Restriction* is the difference-in-difference variable—an indicator equal to one for observations that are exempt from the uptick rule. The control variables include market capitalization and equity book-to-market. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter and are reported in parentheses.

	$RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$		
	Sub Sample: Size		
	Small	Medium	Large
	(1)	(2)	(3)
Pilot Comp.	-0.009	-0.002	-0.015^{**}
	(0.008)	(0.006)	(0.007)
No Restriction	0.001	0.043^{***}	-0.002
	(0.014)	(0.009)	(0.011)
log(Market Cap.)	0.003	0.004	-0.019^{***}
	(0.007)	(0.007)	(0.003)
Book-to-Market	0.005	-0.011	-0.059^{***}
	(0.006)	(0.009)	(0.013)
Quarter FEs	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	10,593	10,603	10,937
R^2	0.594	0.628	0.634

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9: First-stage of Russell reconstitution

This table reports the first-stage of a fuzzy RD for pilot and control stocks during the pilot program. For each Russell year, we follow Chang, Hong, and Liskovich (2014) and estimate the following first-stage equation:

$$R1000_{i,t} = \alpha + b_1(Rank_{i,t} - c_t) + b_2\tau_{i,t} + b_3\tau_{i,t} * (Rank_{i,t} - c_t) + e_{i,t}$$

$R1000_{i,t}$ equals one for firms that are included in the Russell 1000 index, and zero otherwise. $Rank_{i,t}$ is the firm's rank based on its market capitalization on the last trading day of May, in ascending order. c_t is the cutoff rank of the Russell 1000 index and the Russell 2000 index. $\tau_{i,t}$ is the omitted instrument and equals one for firms with rank greater than the cutoff c_t, and zero otherwise. Each column reports results for different bandwidth lengths, where the bandwidth is the number of stocks on either side of the cutoff. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and quarter, and are reported in parentheses.

	R1000					
bw	210	220	230	240	250	260
τ	0.821***	0.829***	0.836***	0.842***	0.848***	0.853***
	(0.061)	(0.058)	(0.056)	(0.053)	(0.052)	(0.050)
Rank-c	0.001**	0.001**	0.001**	0.0005**	0.0005**	0.0004**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\tau\times$(Rank-c)	−0.00003	−0.00002	−0.00002	−0.00001	−0.00001	−0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Year	Year	Year	Year	Year	Year
Observations	779	815	851	888	926	962
R^2	0.958	0.959	0.961	0.962	0.963	0.965

Note: *p<0.1; **p<0.05; ***p<0.01

Table 10: Fuzzy RD for institutional ownership

This table reports the second-stage of a fuzzy RD for pilot and control stocks during the pilot program. For each stock-quarter, we follow Chang, Hong, and Liskovich (2014) and estimate the following two equations:

$$\mathrm{R1000}_{i,t} = \alpha + b_1(\mathrm{Rank}_{i,t} - c_t) + b_2\tau_{i,t} + b_3\tau_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + e_{i,t}$$
$$\mathrm{IO}_{i,t} = \alpha + \beta_1(\mathrm{Rank}_{i,t} - c_t) + \beta_2\widehat{\mathrm{R1000}}_{i,t} + \beta_3\widehat{\mathrm{R1000}}_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + \epsilon_{i,t}$$

The first stage is estimated using the annual Russell reconstitutions, and is applied to the quarterly data for the subsequent Russell-year. For each quarter t, $\mathrm{IO}_{i,t}$ is the institutional ownership level for firm *i*. $R1000_{i,t}$ equals one for firms that are included in the Russell 1000 index, and zero otherwise. $Rank_{i,t}$ is the firm's rank based on its market capitalization on the last trading day of May, in ascending order. c_t is the cutoff rank of the Russell 1000 index and the Russell 2000 index. $\tau_{i,t}$ is the omitted instrument and equals one for firms with rank greater than the cutoff c_t, and zero otherwise. Each column reports results for different bandwidth lengths, where the bandwidth is the number of stocks on either side of the cutoff. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and by quarter, and reported in parentheses.

Panel A: Pilot stocks

	Institutional Ownership					
bw	210	220	230	240	250	260
$\widehat{R1000}$	0.117*	0.114*	0.112*	0.116**	0.112**	0.097*
	(0.064)	(0.061)	(0.058)	(0.057)	(0.055)	(0.053)
Rank-c	−0.0004	−0.0005*	−0.001**	−0.001**	−0.001***	−0.001**
	(0.0003)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
$\widehat{R1000}$×(Rank-c)	−0.0003	−0.0001	−0.00001	0.0001	0.0002	0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	954	1,005	1,044	1,092	1,147	1,179
R^2	0.933	0.935	0.935	0.937	0.938	0.936

Panel B: Control stocks

	Institutional Ownership					
bw	210	220	230	240	250	260
$\widehat{R1000}$	−0.044	−0.057	−0.055	−0.046	−0.050	−0.058*
	(0.039)	(0.038)	(0.037)	(0.036)	(0.035)	(0.035)
Rank-c	0.0004*	0.0004**	0.0004**	0.0003**	0.0003*	0.0003**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\widehat{R1000}$×(Rank-c)	−0.001**	−0.001**	−0.001**	−0.001**	−0.0004*	−0.0004**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	2,109	2,197	2,303	2,403	2,497	2,605
R^2	0.923	0.924	0.924	0.923	0.924	0.922

Table 11: Fuzzy RD for information intensity

This table reports the second-stage of a fuzzy RD for pilot and control stocks during the pilot program. For each stock-quarter, we follow Chang, Hong, and Liskovich (2014) and estimate the following two equations:

$$\mathrm{R1000}_{i,t} = \alpha + b_1(\mathrm{Rank}_{i,t} - c_t) + b_2\tau_{i,t} + b_3\tau_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + e_{i,t}$$
$$\mathrm{II}_{i,t} = \alpha + \beta_1(\mathrm{Rank}_{i,t} - c_t) + \beta_2\widehat{\mathrm{R1000}}_{i,t} + \beta_3\widehat{\mathrm{R1000}}_{i,t} * (\mathrm{Rank}_{i,t} - c_t) + \epsilon_{i,t}$$

The first stage is estimated using the annual Russell reconstitutions, and is applied to the quarterly data for the subsequent Russell-year. For each quarter t, $\mathrm{II}_{i,t}^{avg}$ is the information intensity measure for firm i. The information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. $R1000_{i,t}$ equals one for firms that are included in the Russell 1000 index, and zero otherwise. $Rank_{i,t}$ is the firm's rank based on its market capitalization on the last trading day of May, in ascending order. c_t is the cutoff rank of the Russell 1000 index and the Russell 2000 index. $\tau_{i,t}$ is the omitted instrument and equals one for firms with rank greater than the cutoff c_t, and zero otherwise. Each column reports results for different bandwidth lengths, where the bandwidth is the number of stocks on either side of the cutoff. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and by quarter, and reported in parentheses.

Panel A: Pilot Stocks

	Information Intensity					
bw	210	220	230	240	250	260
$\widehat{R1000}$	0.034	0.055**	0.039	0.042**	0.048**	0.045**
	(0.025)	(0.023)	(0.024)	(0.021)	(0.021)	(0.021)
Rank-c	−0.0002	−0.0004**	−0.0003	−0.0003	−0.0003	−0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\widehat{R1000}$×(Rank-c)	0.00002	0.0002	0.0002	0.0001	0.00004	0.00004
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	954	1,005	1,044	1,092	1,147	1,179
R^2	0.637	0.643	0.641	0.640	0.641	0.642

Panel B: Control Stocks

	Information Intensity					
bw	210	220	230	240	250	260
$\widehat{R1000}$	0.013	0.007	−0.010	−0.009	−0.006	−0.006
	(0.026)	(0.024)	(0.022)	(0.022)	(0.023)	(0.023)
Rank-c	0.0002	0.0002	0.0003**	0.0002*	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\widehat{R1000}$×(Rank-c)	−0.0003	−0.0002	−0.0002	−0.00004	0.00000	0.00003
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	2,109	2,197	2,303	2,403	2,497	2,605
R^2	0.651	0.653	0.653	0.653	0.654	0.656

Note: *p<0.1; **p<0.05; ***p<0.01

Table 12: Placebo fuzzy RD for information intensity

This table reports the second-stage of a fuzzy RD for pilot and control stocks from 2002 to 2005, before the pilot program. For each stock-quarter, we follow Chang, Hong, and Liskovich (2014) and estimate the following two equations:

$$\mathrm{R1000_{i,t}} = \alpha + \mathrm{b_1}(\mathrm{Rank_{i,t}} - \mathrm{c_t}) + \mathrm{b_2}\tau_{\mathrm{i,t}} + \mathrm{b_3}\tau_{\mathrm{i,t}} * (\mathrm{Rank_{i,t}} - \mathrm{c_t}) + \mathrm{e_{i,t}}$$
$$\mathrm{II_{i,t}} = \alpha + \beta_1(\mathrm{Rank_{i,t}} - \mathrm{c_t}) + \beta_2\widehat{\mathrm{R1000}}_{\mathrm{i,t}} + \beta_3\widehat{\mathrm{R1000}}_{\mathrm{i,t}} * (\mathrm{Rank_{i,t}} - \mathrm{c_t}) + \epsilon_{\mathrm{i,t}}$$

The first stage is estimated using the annual Russell reconstitutions, and is applied to the quarterly data for the subsequent Russell-year. For each quarter t, $\mathrm{II_{i,t}^{avg}}$ is the information intensity measure for firm i. The information intensity is the ratio of the post-announcement realized variance divided by the total return variance in the pre- and post-announcement period: $RV_{i,t}^{T-1,T+2}/RV_{i,t}^{T-22,T+2}$. Realized variances are defined as the sum of squared daily returns. $R1000_{i,t}$ equals one for firms that are included in the Russell 1000 index, and zero otherwise. $Rank_{i,t}$ is the firm's rank based on its market capitalization on the last trading day of May, in ascending order. c_t is the cutoff rank of the Russell 1000 index and the Russell 2000 index. $\tau_{i,t}$ is the omitted instrument and equals one for firms with rank greater than the cutoff c_t, and zero otherwise. Each column reports results for different bandwidth lengths, where the bandwidth is the number of stocks on either side of the cutoff. Observations with prices less than $5 at the beginning of the period are dropped. All standard errors are clustered by firm and by quarter, and reported in parentheses.

Panel A: Pilot Stocks

	Information Intensity					
bw	210	220	230	240	250	260
$\widehat{R1000}$	0.020	0.024	0.027	0.023	0.025	0.022
	(0.037)	(0.033)	(0.031)	(0.030)	(0.029)	(0.028)
Rank-c	−0.00000	−0.0001	−0.0001	−0.0001	−0.0002*	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\widehat{R1000}$×(Rank-c)	−0.00005	0.0001	0.0001	0.0001	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	1,381	1,462	1,522	1,580	1,643	1,725
R^2	0.601	0.601	0.601	0.603	0.605	0.606

Panel B: Control Stocks

	Information Intensity					
bw	210	220	230	240	250	260
$\widehat{R1000}$	0.042*	0.039	0.038	0.038	0.045*	0.039
	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.027)
Rank-c	−0.00004	−0.00001	0.00001	0.00002	−0.0001	−0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\widehat{R1000}$×(Rank-c)	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter	Firm,Quarter
Observations	3,027	3,160	3,306	3,453	3,615	3,744
R^2	0.609	0.607	0.607	0.606	0.606	0.606

Note: *p<0.1; **p<0.05; ***p<0.01