How Quickly Do Markets Learn? Private Information Dissemination in a Natural Experiment[☆]

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First Version: December 2014

This Version: April 2015

[☆]The authors thank Jennifer Arlen, Ian Ayres, Lucian Bebchuk, Emiliano Catan,John Coffee, Martijn Cremers, Slava Fos, Merritt Fox, Lawrence Glosten, Jeffrey Gordon, Kevin Haeberle, Scott Hemphill, Charles Jones, Jonathan Macey, Roberta Romano, Sarath Sanga, Richard Squire and Paul Tetlock for helpful discussions and suggestions. This project has benefited a great deal from feedback at seminars at Columbia, Harvard, NYU, Pittsburgh, and Yale. We are grateful to the Ira M. Millstein Center for Global Markets and Corporate Ownership for financial support that made our PDS subscription, and this research, possible. We thank Brian Benvenisty and Like Chen for excellent research assistance. Please send your comments to robert.jackson@law.columbia.edu (Jackson), wj2006@columbia.edu (Jiang) or joshua.mitts@law.columbia.edu (Mitts).

How Quickly Do Markets Learn?

Private Information Dissemination in a Natural Experiment

Abstract

This study takes advantage of a unique episode in which the SEC distributed securities filings to a small group of investors ahead of their public releases. The random delay time provides a rare natural experiment for examining how markets process new private information. It takes minutes – not seconds – for informed traders to incorporate fundamental information into stock prices. The early-informed convey more information into stock prices when the delay before public release is longer. More importantly, the rate at which information is impounded into prices is more correlated with the length of the *predicted* delay than with the *actual* delay.

1. Introduction

For more than two decades, the Securities and Exchange Commission (SEC) has provided investors with access to securities filings containing market-moving information through its Electronic Data Gathering, Analysis, and Retrieval, or EDGAR, system, which is available through the SEC's website. For years, however – unbeknownst to most investors, lawmakers, and the public – a small group of private investors has consistently been given early access to these filings before they are released via EDGAR. A government contractor operating a service known as the public dissemination service, or PDS, distributed SEC filings to a small number of paying subscribers moments before they reached the public. In October 2014, the Wall Street Journal exposed the issue,[1] drawing immediate demands from Members of Congress that the SEC examine the problem.[2] Two months later, SEC Chairman Mary Jo White pledged to Congress that the Commission would soon eliminate PDS subscribers' advantage.[3]

While investors' and lawmakers' outrage in response to these revelations was understandable, we were more intrigued by a rare opportunity presented by the episode. Before the problem was revealed to the public, Jackson and Mitts (2014) designed and implemented software that tracks the moment when filings reach PDS subscribers and the public EDGAR website. The data effectively give us a lab-like setting for studying how speculators trade on, and how the stock market processes, private information. Specifically, the setting gives

[1] A *Wall Street Journal* article published on October 30, 2014 entitled "Fast traders are getting data from SEC seconds early: studies show lag in posting to website" (by Scott Patterson and Ryan Tracy) was the first to reveal the PDS advantage to the public. Before this issue was revealed, Jackson and Mitts subscribed to the PDS service in order to study the effects of the early dissemination of market-moving information. They provided detailed analysis of the timing of the delivery of filings through the SEC's systems that was featured in that article as a critical piece of evidence.

[2] For example, U.S. Senators Tim Johnson and Mike Crapo, the Chairman and Ranking Member of the Senate Committee on Banking, Housing, and Urban Affairs, respectively, wrote to SEC Chairman Mary Jo White lamenting the "unequal access" to information provided on SEC-managed systems and demanding that the SEC take steps to "understand and eliminate this disparity."

[3] Chairman White's letter, sent in December 2014, specified that the SEC would, by early 2015, "implement[] an enhancement to our system...to ensure that EDGAR filings are available to the public on the SEC website before such filings are made available to PDS subscribers."

us the following two features that are typically not available to researchers in this area.

First, we are able to detect both the arrival as well as the nature of private information. While the theoretical literature (pioneered by Glosten and Milgrom (1985), Kyle (1985), and Back and Baruch (2004)) has developed a thorough framework for how securities prices incorporate private information through the work of informed traders, there are few direct empirical tests of these important theories. That is because private information is, by definition, not public knowledge; thus, neither the timing of its arrival, nor its content, is observable by econometricians.[4] In our setting, we observe the exact time of the arrival of information to a small group of investors (the time at which the filing first reaches PDS subscribers) as well as the nature of the information the investors receive (the content of the filings).

Second, we are able to measure how long informed traders have the information before the filings reach the public – that is, we can detect the beginning and the end of the window during which informed traders can take advantage of their information. Critically, as explained below, the duration of the "private window" in our setting varies randomly, allowing us to identify the incorporation of private information in a quasi-experimental setting. Although the SEC initially claimed that PDS subscribers received filings "at the same time" as filings were posted to the SEC's website, in fact the technical limitations of the EDGAR system led to delays of random length between the time when PDS subscribers received filings and when those filings were posted to EDGAR.[5] The variation in the length of the "private window" in our setting is thus exogenous in the sense that it was beyond the control of all of the parties involved and is not correlated with any of our variables of

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[4]Cornell and Sirri (1992) was an exception in that it presents a clinical study of an illegal insider trading case using ex post court records.

[5]The length of the delay did depend, in part, upon the volume of filings being submitted to the systems throughout the day. In particular, the delay was longest at approximately 4:00 PM Eastern Standard Time, when markets close – and these systems tend to be overwhelmed by the volume of submissions. As we explain in further detail below, however, the time of day was only a noisy predictor of the length of the "private window," which was otherwise random.

interest. This unique source of exogenous variation allows us to draw rare causal inferences about the process through which markets incorporate information into public-company stock prices.

Our study includes three principal findings. First, as one might predict, we find that the potential profits available to informed traders increase with the length of the delay until the information becomes public. We find that informed traders encountered profit opportunities ranging from six to nine basis points per 100-second delay across our entire sample of filings. As one might also anticipate, the gains are significantly larger for the subset of filings that are especially "newsworthy:" we identify 576 filings (about 7 per day, on average) that generate an absolute abnormal return of more than 2% from the moment when private investors receive the information until the next day's market close.

Second, we find that informed traders take several minutes – not seconds – to impound new fundamental information into stock prices. Contrary to popular intuition driven by the high-frequency trading that has captured headlines, we show that, unlike trading information such as order flow, fundamental information is not incorporated into stock prices in seconds. Indeed, we observe little price impact during the first 100 or so seconds of the "private window," and it takes five to six minutes of trading by informed investors for stock prices to impound just half of the total effect of the information. In addition, we find that privately informed investors impound significantly more private information into stock prices during the period when those investors would expect there to be a private window than during unexpected portions of that window. That finding is consistent with the notion, previously advanced in the theoretical literature, that informed investors engage in strategic trading – that is, that such investors attempt to maximize profits by smoothing out the price impact of their trading over the expected time during which they will have an informational advantage (Caldentey and Stacchetti (2010)).

Finally, we analyze whether informed trading leads investors to "overreact" to the public release of information on the EDGAR website because the public is unaware that the information is stale. We find that a significant proportion (about 20% to 30%) of the abnormal return we observe after filings are posted to the EDGAR website is reversed during the subsequent four days – but only in cases where the delay between the private and public release of the information was more than 100 seconds. To the extent that the duration of the private window is positively correlated with the staleness of the information when it was released to the public, it is not surprising that the reversal is generally increasing in the length of the delay. The lack of a return reversal (reflecting an overreaction) when the delay was brief – that is, when the time between private and public release of the information was 100 seconds or less–suggests that the only reason for the overreaction in the other cases was public investors' ignorance of the early leakage.

Our study makes a distinct contribution to the vast literature on information transmission and asset pricing, and in particular, by making the usually unobservable private information the subject of our empirical tests – in contrast to more common approaches that rely on transaction and order flow information (for comprehensive surveys, see Easley and O'Hara (2003), Biais et al. (2005), and Tetlock (2014)). Given the fundamental role of financial markets in the aggregation of information and allocation of investment capital (for a detailed survey, see Bond et al. (2012)), our study sheds light on exactly how the stock market performs that role. Importantly, our study complements, but is distinct from, several recent papers that assess the relationship between the distribution of information to investors through the internet and price discovery (Bauguess et al. (2013), Drake et al. (2014), Loughran and McDonald (2014)), because the subject of our study is private – rather than public – information.[6]

[6]Two other recent working papers analyze market responses to private information before its public release (Hu et al. (2013) and Rogers et al. (2014)). As explained above, however, our setting features random variation which is not the case in Hu et al. (2013). Rogers et al. (2014) analyzes the same episode as we do, but that study covers only one of the many types of SEC filings (Form 4) and does not explore the random variation in the private-information window.

The recent work most relevant to our study is likely Collin-Dufresne and Fos (2014a) and Koudijs (2014a,b), all of which adopted ingenious research designs to identify the path of private information and its effect on stock prices. Our design differs from that of Collin-Dufresne and Fos (2014a) in that the private information in our study relates to the financial and operational – that is, the fundamental – condition of the firm itself. By contrast, the private information studied in Collin-Dufresne and Fos (2014a) is about the trader's intention to intervene rather than about the current state of the firm. As a result, both the creation and duration of the private information are endogenous to the informed trader, which imply critically different strategic behaviors in trading on private information (Collin-Dufresne and Fos (2014b)).

More closely related to our work is Koudijs (2014a,b), which use boats carrying mail between London and Amsterdam during the 18th century as the conduit for information flow to the stock exchanges in both cities to uncover the strategic behavior of informed traders. Like Koudijis, we study how information reaches and is processed by markets, although we use electronic dissemination as the 21st-century equivalent of boats as transmitters of information. Also like Koudijis, we take advantage of an exogenous source of random variation – in our case, random delays in electronic transmission, and in his, inclement weather that delayed boats at random – to identify how markets process private information. Over the course of the last three centuries, boat journeys that took weeks have been replaced by electronic signals that reach their destinations in seconds as the means for disseminating value-relevant information to investors. We believe that studying similar episodes from these two different eras will offer new insights as to how stock markets have processed private information in the past, and how they might do so in the future.

2. Data and Summary Statistics

2.1. Data

U.S. securities laws impose rigid rules on publicly traded companies, requiring these firms to disclose material information about themselves to investors in a timely manner. These disclosures are typically provided in the form of securities filings submitted to the SEC. As a result, the SEC has become a central repository for information that moves markets. Specifically, the SEC's EDGAR system, first launched in the 1990s, is the central portal through which firms can disclose, and investors can retrieve, new information about a firm's fundamental value.

At the time of this study, when a company electronically submits a securities filing to the SEC, the filing is distributed to three locations. The first location is the SEC's file transfer protocol (FTP) server. At the same time, a private contractor operates a service known as the "public dissemination service," or PDS, which distributes the filing to a small group of about forty subscribers at a cost of approximately $15,000 per year. Finally, the filing is uploaded to the SEC's EDGAR system, which is available to the investing public through the SEC's website. While in theory these systems should operate simultaneously, in fact technical limitations of these systems led to random delays between the time when filings were distributed to PDS subscribers and when they were made available to the public on EDGAR. Indeed, the dissemination pipeline to the EDGAR website was exceptionally prone to delays. Thus, investors with access to the SEC's FTP server, or with a PDS subscription, received filings before other investors could access those filings on the SEC's EDGAR website. The length of the delay before filings reached the EDGAR website over the period we study ranged from a few seconds to as long as several minutes.

Our study builds on previous work by two of the authors, who collected a detailed dataset including the exact timestamps when filings were posted to the FTP server, distributed to PDS subscribers, and made available on the EDGAR website from June

25 to October 15, 2014.[7] Using the overlapping part of the sample, we found that the FTP and PDS time stamps are almost identical, featuring differences of no more than a few seconds. As such, we use the FTP timestamp as a proxy for the time advantage of the "early informed" in order to preserve a larger sample. Thus, for purposes of our study, sophisticated investors could become a member of the early informed either by directly accessing the FTP site or subscribing, for a fee, to the PDS service. Our sample period ends right before the revelation of the PDS advantage because the time gap shrank precipitously afterwards (though did not completely disappear). Figure 1 shows the percentage of filings released to PDS before EDGAR from August 2014 to April 2015 using a "heatmap" monitored in real time.

[Insert Figure 1 here.]

This group of informed investors is expected to be small relative to the number of all market participants. During the period we study, the PDS service had about forty paying subscribers. There is anecdotal evidence suggesting that some of these PDS subscribers were wire services,[8] but end-users likely did not have real-time access to the original filings. These wire services disseminate brief summaries of the original filing quickly, but by the time these services are able to write and post new articles, the filings are typically available on the EDGAR website.[9] With respect to early access via FTP, utilizing the FTP server to

[7]Our data for delivery to PDS subscribers begins on August 1, 2014, and continues through the end of the sample period. We obtained the EDGAR website timestamp by monitoring the RSS version of the "Latest Filings" feed that the SEC provides to the public. The FTP timestamp was obtained by querying the FTP server for the last modified date of the filing. The PDS timestamp was obtained by recording the exact time a filing was delivered to the PDS subscription maintained by Jackson and Mitts (for a description of that process, see Jackson and Mitts (2014)). We also recorded the timestamp indicating when each filing was accepted by the SEC, which likely reflects the time when the filing was uploaded to the SEC's servers before it is disseminated through FTP and the SEC's website.

[8]The SEC declined to provide a list of subscribers. According to news reports, the group of PDS subscribers includes several major financial news and data providers, including Dow Jones Newswire and Morningstar, Inc. See "Gap narrows in access to SEC filings" (by Andrew Ackerman, Scott Patterson, and Ryan Tracy), *Wall Street Journal*, November 3rd, 2014.

[9]It is possible that information contained in the filing we study may have, in some cases, been released before the filing itself was submitted to the SEC. For example, companies occasionally announce earnings in press releases prior to formal SEC filings. This possibility works against our findings as in such cases

detect unexpected filings is technically difficult, as an interested investor would be required to navigate, without any delay, to the server directory associated with a particular firm. Because it is difficult to know ex ante which firms will file unexpected or unscheduled filings – which constitute about 95% of our sample – we think that the number of investors with early access to filings via FTP is relatively small.[10]

2.2. Sample

Our entire dataset includes 101,555 securities disclosures that public companies electronically filed with the SEC from June 25, 2014 to October 15, 2014, with the exception of July 15, 2014, as technical difficulties with connecting to the SEC's systems prevented us from collecting data on that day. As most of these filings were made by firms whose shares are not traded on a public exchange, we limit our sample to only those filings made by publicly traded firms. To determine whether a firm is publicly traded, we search for an entry for the firm in the CRSP and Compustat table that links an entity's CIK to its exchange ticker. In addition, we remove filings that arrived on the EDGAR website prior to the FTP server, which occurred only occasionally. We also remove filings that occur within one day of a previous filing by the same issuer. These filters reduce our sample to 42,619 filings.

For each filing, we obtain individual trades in the issuer's primary shares from the NYSE TAQ database, beginning at the FTP timestamp and concluding 10 minutes following the EDGAR website timestamp. Restricting the sample further to filings having at least

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information might already be stale by the time it reaches the PDS subscribers.

[10] It is possible, however, to observe the "file created" date ex post and thereby identify the time that a filing is deposited on the FTP server. Indeed, the authors used that process to identify the FTP timestamps used in this study. After the public revelation of the delay in posting filings to the EDGAR website, however, the authors' requests to FTP servers were frequently denied during the trading day. The SEC's servers responded to these requests with an error message stating that the maximum number of clients allowed on the FTP server (50) were already connected. By contrast, similar requests before the public revelation of this issue were never denied due to server overload. These facts suggest that relatively few investors were attempting to access the FTP server during the period that we study – and that more investors started to pursue access via FTP after the PDS advantage was revealed to the public.

one trade in the TAQ data during the lag between the FTP and EDGAR timestamps further reduces the sample size to 3,394 filings, or about 8% of the total filings by public companies during our sample period. This relatively small percentage was mainly due to two causes. First, most of the filings involve issuers with low trading volume throughout the day. Second, in most of the remaining cases, the random delay between the FTP timestamp and the arrival of the filing on the EDGAR website was too short for the early informed to react before the information became public. For example, the median delay for filings without a trade between the FTP and EDGAR timestamps was 22 seconds, compared to 151 seconds among filings with at least one trade during the FTP-EDGAR gap.

Filings with trades after the FTP timestamp – but before the public release of the information on EDGAR – constitute our key sample for most of the analyses described below. This sample includes 140 different filing types, where the most common are Form 8-K (timely disclosure of material corporate events), Form 4 (disclosure of insiders' trades in the company's stock; current U.S. securities law requires insiders to provide such disclosure within 48 hours of each trade), and Schedule 13D (disclosure of beneficial ownership of 5% or more; current law requires this Schedule to be filed within 10 days after the investor crosses the 5% threshold). These three form types combined make up 70.3% of the sample. Moreover, a great majority (94.7%) of the filings in our sample is non-scheduled: that is, they are contingent on unanticipated events rather than a predetermined filing date (unlike, for example, Forms 10-Q and 10-K, which are filed within a specified time following the conclusion of the company's fiscal quarter or fiscal year, respectively). This is important for our analysis because investors could not have anticipated the arrival of the overwhelming majority of the filings we study.

To set the stage, we define the following key points in the timeline of events with respect to each individual filings:

[Insert Figure 2 here.]

t_1: The PDS/FTP timestamp, or the time when the "early informed" receive the information.

t_2: The EDGAR timestamp, or the time when the filing information becomes public. The difference $(t_2 - t_1)$ is thus the "private window," or the time lag during which the information remains private.

t_3: A time proxy for the end of the period (t_2, t_3) during which public investors trade on the information revealed by the SEC filing.

t_4: A time proxy for the time by which the stock price fully incorporates the new information, including properly adjusting potential initial over-/under-reaction.

2.3. Summary statistics

Table 1 reports the distribution of the *Delay*, $(t_2 - t_1)$, in seconds, for the full sample of 42,619 filings, as well as separately for the three major filing types. The median delay for the full sample is 26 seconds, with an interquartile range of 7 to 172 seconds. The distributions are highly right-skewed, leading to both mean and variance values that are not representative of the sample. Unless otherwise specified, we impose an additional filter for sample inclusion that *Delay* must not exceed 466 seconds, or the 90th percentile value of the full sample. Trimming these outliers not only limits the influence of extreme observations but also takes into account the possibility that the monitoring script may have periodically "hung" due to server overload, introducing erroneous delays into the data. We believe that the top decile reflects a conservative estimate of delays that are likely to be erroneous, but our results are robust using a reasonable higher or lower cutoff. The last two rows of Table 1 report the truncated mean (131 seconds) and standard deviation (129 seconds), which reflect the central and dispersion tendencies of the trimmed sample.

[Insert Table 1 here.]

While the delay between early and public release of filings is largely random, it does seem to be affected by the volume of submissions and traffic at the SEC's EDGAR servers.

In fact, there is quite a distinct pattern of *expected* delay in relation to the time of the day. Figure 3 demonstrates the daily pattern with an average plot of $(t_2 - t_1)$ by hourly bins from 6:00am to 9:00pm as well as the intensity of filings throughout the day. The average delay reaches its peak (over 250 seconds) right after 4:00pm EST, the close of the trading day on the formal market – presumably a time with high filing traffic, causing delays in the transmission of filings to the public EDGAR servers. Critically, however, the distribution of the delay remains largely random conditional on the time of day: indeed, the time of day explains only 8.6% of the total variance in the delay for the final sample of filings.

[Insert Figure 3 here.]

It is worth noting that trades take place before the market opens at 9:30am and continue after the close of the market at 4:00pm. These after-hours trades, including preopen (8:00–9:30am) and post close (4:00–6:30pm), are not a recent phenomenon; trades have been executed regularly during these hours on electronic communications networks (ECNs) for decades. For example, Barclay and Hendershott (2003) document that, among the 250 highest-volume stocks on the Nasdaq exchange in 2000, about 2.5% of the trading volume occurs pre-open and another 5.5% post-close. Pre-open and post-close trades account for 4.0% and 9.9% of our final sample. Our sample's over-representation of after-hours trades is consistent with Barclay and Hendershott's (2003) finding that adverse selection in trading starts at higher levels during the early part of the day, decreases over the course of the regular trading day, and increases immediately following the close of the market.

Importantly, the time of the day seems to be the only effective (and still noisy) predictor of the FTP-public delay. We further verify that neither the actual delay nor the expected delay (as a function of the time of the day) is meaningfully correlated with firm characteristics such as market capitalization, trading liquidity, and return volatility. Nor is the actual delay or the expected delay affected by the filings themselves. For example, the correlation between the frequency of filings with at least one trade between (t_1, t_2) (see

Figure 3) and the average delay is actually slightly negative (-0.07), indicating that the final sample for our analyses are not distributed in synchronization with the delay patterns. The correlation between the size (measured by the full file size or by text bytes) and the length of the delay between the FTP and EDGAR timestamp is even closer to zero (-0.004), alleviating the concern that file size – a commonly used proxy for content complexity – might be endogenous to the delay. To summarize, the FTP-public delay, conditional on the time of the day, appears to be random. Moreover, the expected delay and the actual delay, conditional on the time of day, are not driven by the characteristics of individual issuers or the nature of the filings in our sample. Thus, the quasi-random nature of the delay gives us an unusual opportunity to draw causal inferences from the episode that we study.

The variables of central interest to this study are the abnormal returns earned during various time windows. Therefore, the sample for our continuing analyses is restricted to all filings for which there is at least one trade during (t_1, t_2), i.e., the sample with the possibility of trading on private information. The unconditional probability for a filing by a public company to be included in our final sample is 6.02%. Table 2 begins with summary statistics for the main determinants for sample inclusion, followed by an estimation of the following cross-sectional model using the logit specification:

$$\begin{aligned} Inclusion_i = & \beta_1 Delay_i + \beta_2 After\ hours_i + \beta_3 MVDecile_i + \beta_4 Illiquidity_i \\ & + \beta_5 Idiovolatility + \vec{\lambda} Filing\, type_i + \epsilon_i. \end{aligned} \tag{1}$$

In (1), i is an index for individual filings; $Inclusion$ is a dummy variable equal to one if filings i is included in our final sample (i.e., has at least one trade during the private window); $Delay$ is the length of $t_2 - t_1$ in the unit of 100 seconds; $After\ hours$ is a dummy variable equal to one if the filing occurs outside of the regular exchange trading hours (before 9:30am or after 4:00pm); $MVDecile$ is the market capitalization decile ranking of the issuer as of June 30, 2014; *Illiquidity* is the Amihud (2002) illiquidity measure, estimated as the average daily $1000\sqrt{|Return|/(DollarTradingVolume)}$; and *Idiovolatility* is the annualized idiosyncratic volatility from the Fama and French (1993) plus Carhart (1997) four-factor model. The last two variables are constructed using daily data from July 1, 2013 to June 30, 2014. Finally, *Filing type* is a vector of dummy variables for the main filings types, i.e., Form 8-K, Form 4, and Schedule 13D.

[Insert Table 2 here.]

The relations described in Table 2 are all consistent with intuition, and offer some detail on the nature of our sample. In a logit regression, the exponentiated coefficients represent "odds ratios," i.e., the incremental change in $Pr(Inclusion)/[1 - Pr(Inclusion)]$ associated with a one-unit change in the regressor. We derive the marginal probability associated with each determinant based on the odds ratio and the unconditional probability of file inclusion in the final sample (6.02%). To begin, longer delays invite more trades, and hence increase the probability of inclusion in our sample: every 100 seconds of delay increase the probability of a trade during the private window by 4.6 percentage points. Relatedly, filing outside of the regular exchange trading hours reduces the probability of trading by 5.9 percentage points.[11] As expected, market capitalization, trading liquidity, and firm-specific return volatility all positively and significantly (at the 1% level) predict the occurrence of trades. Finally, our final sample includes disproportionately more Form 8-K's, and disproportionately fewer Form 4's, presumably because the former are informationally richer than the latter and hence trigger more trading on average.

For an overview, we plot in Figure 4 the histogram of the average abnormal return during the private window, (t_1, t_2), where the benchmark return is that of the SPY, the most liquid exchange-traded fund (ETF) tracing the S&P 500 index. That is: $AR_i(t_1, t_2) =$

[11] There were 1,513 filings during trading hours (i.e., 9:30am to 4:00pm) with a delay between the FTP and EDGAR timestamps that had no trade during (t_1, t_2) but at least one trade during $(t_1, t_2 + 10\,\text{min})$. For this sample, the average (median) delay is 73 (23) seconds.

$R_i(t_1, t_2) - R_m(t_1, t_2)$. The mean is essentially zero (0.005 basis points), and the standard deviation is 35 basis points (after winsorizing at the 1% extremes). Figure 4 shows that the abnormal returns are roughly symmetric and have fatter tails than a comparable normal distribution.

[Insert Figure 4 here.]

3. Abnormal Returns and Information Dissemination

3.1. Returns during the "private window"

3.1.1. Regression analysis

Given that the "private window" granted some trading participants early access to SEC filings, the first natural question to explore is the profitability that such an opportunity gives informed traders. To this end, we compute the abnormal returns during the gap between the time when the early informed receive information (the FTP timestamp, or t_1) and the time of public release of the same filing (the public server time, or t_2), and relate them to the length of the delay, conditional on the sign of the ex post returns that incorporate the market's reaction to the news. The linear regression model is as follows:

$$AR_i(t_1, t_2) = \beta_1 Delay_i + \vec{\lambda} Filing\,type_i + \alpha_t + \epsilon_i. \tag{2}$$

In this analysis, the dependent variable is $AR_i(t_1, t_2)$, the abnormal returns (in basis points) of stock i during the time window when information remains private. The benchmark return is that of SPY, the exchange-traded fund (ETF) for the S&P 500 index portfolio. The choice of SPY over a broader based market portfolio reflects the need to have an instrument with sufficient trading liquidity at high frequencies. Given our interest in assessing how information is disseminated through trading, we include in this analysis only observations where stock i posts at least one transaction during the interval (t_1, t_2) in the TAQ trading data. The key independent variable is *Delay*, which is $(t_2 - t_1)$ in seconds. Moreover, some of the specifications for (2) also include dummy variables for major filing types as well as a daily fixed effect.

We adopt both a short and a long window, (t_2, t_3), to allow the market to digest new information from the public release of the filings after t_2, resulting in two abnormal return measures capturing the information content of the filings for the short term. Henceforth we denote $t_3 = \{t_2 + 10\,\text{min}, d_1\}$ as the point of time when we record the new value of the security after the market digests the publicly released information. The two resulting measures, $AR_i(t_1, t_2 + 10\,\text{min})$ and $AR_i(t_1, d_1)$, represent abnormal returns from the early access time to 10 minutes after the public release, or to the market close of the following day, respectively.

Table 3 reports the relation between $AR_i(t_1, d_1)$ and *Delay*, conditional on positive and negative news, where the latter is simply classified by the sign of $AR_i(t_1, d_1)$. In Panel A, the end of the period during which the market digests the public information, t_3, is set to be the market close of the following day, d_1. In both directions, for every 100 seconds of incremental delay, the private informed traders gain an additional 6.2–8.6 basis points in profits. The magnitude of the gain is stable across all specifications, whether or not we include controls for file types and daily fixed effects, and are all statistically significant at the 1% level.

[Insert Table 3 here.]

Needless to say, the returns we see in Table 3 – that is, returns conditional on the sign of the ex post return $AR_i(t_1, t_3)$ – are not fully attainable from a tradeable strategy for two reasons. First, as t_2 gets closer to t_3, $AR_i(t_1, t_3)$ becomes more correlated with $AR_i(t_1, t_2)$ regardless of the information content of the filing delivered to the privately informed at t_1. If one were to condition returns on the sign of $AR_i(t_1, t_2)$, its magnitude would be closely mapped to volatility, which is a monotonic function of $\sqrt{t_2 - t_1}$. In unreported simulations, we find that this mechanical effect becomes undetectable when $t_3 = d_1$. This is because the variance of return during (t_2, d_1) (at least a full trading day) overwhelms that during (t_1, t_2) (in seconds and minutes) if the returns in the two periods are uncorrelated under the null of no information. Hence, the results associated with $t_3 = d_1$ (that is, those reported in Panel A of Table 3) should be largely free from the mechanical effect that return volatility increases with time.

Second, the early informed may not always bet in the right direction even given their private access to information, especially when the signal from a filing is not especially strong. To address this issue, we increase the hurdle for positive/negative news classification by requiring $AR_i(t_1, d_1)$ to be more than 0.5%, 1%, and 2% in absolute value. The assumption motivating this analysis is that, if a filing is highly newsworthy ex post, it should be relatively straightforward for speculators to identify the right direction in which to place their bets. Indeed, the coefficients on *Delay* (with full controls) increase smoothly and monotonically, from 7 to 26 basis points per 100 second delay for positive news, and from 9 to 25 basis points for negative news, as the filings become more informative.

Importantly, the profit opportunities during the private window do not depend on the eventual equilibrium stock price that the market settles at one day after the public release of the information. Instead, the early informed can always front-run trades by the late informed, who were likely not aware of their information disadvantage. We thus consider an alternative positive/negative news classification using $AR_i(t_1, t_2 + 10\,\text{min})$, the abnormal returns during the shorter window until 10 minutes after the public release. This interval is meant to provide just enough time for the early informed to unwind their positions by trading against the late informed shortly after the information becomes public. In Panel B of Table 3, t_3 is set to be $t_2 + 10\,\text{min}$, and the coefficients on *Delay* range from 7.1 to 9.3 basis points per 100 seconds of delay, again all significant at the 1% level. If we use a more stringent cutoff $|AR_i(t_1, t_2 + 10\,\text{min})| > 1\%$,[12] the coefficients rise to 36–94 basis points (significant at the 5% level or less), suggesting substantially higher profit opportunities from early access to more informative filings.

3.1.2. Nonparametric analysis

The results in Table 3 offer an overview of the average rate of abnormal returns under the assumption of a linear relation with the time of delay. To entertain possible non-linear progress due to, for example, lags needed for the market price to incorporate private information, we resort to nonparametric analyses by running standard kernel regressions of the abnormal return, $AR(t_1, t_2)$, on the delay, $t_2 - t_1$, conditional on the nature of the news, which we proxy for using the sign and magnitude of the ex post abnormal return, $AR(t_1, t_3)$.

$$\begin{aligned} AR_i(t_1, t_2) &= f^{+}(Delay_i) + \epsilon_i, \text{if } AR_i(t_1, t_3) > 2\%; \\ AR_i(t_1, t_2) &= f^{-}(Delay_i) + \epsilon_i, \text{if } AR_i(t_1, t_3) < -2\%. \end{aligned} \tag{3}$$

For these regressions, t_3 is set to be d_1. Panels A and B of Figure 5 provide a visualization of the cumulative trading profitability as the delay between the FTP timestamp and the public release of information grows longer. We provide separate visualizations of cumulative trading profits for "extreme" positive and negative news using the $|AR_i(t_1, d_1)| > 2\%$ cutoff.

[Insert Figure 5 here.]

The solid lines in the figures are the nonparametric regressions of $AR_i(t_1, t_2)$ versus *Delay* using the standard Gaussian kernel function, and the dotted lines represent the

[12] We opt for 1% rather than 2% as the threshold for "extreme" news because the subsample of observations with absolute abnormal returns greater than 2% is too small for reliable statistical analysis.

90% confidence intervals obtained using bootstrapping with replacement. Several patterns emerge that are incremental to what can be learned from the regressions in Table 3. First, we document an immediate, but small, reaction in stock prices in the very first second – that is why both graphs have a non-zero intercept – followed by a region of "inaction" with little price movement during the next 100 seconds of delay, even for this sample of relatively newsworthy events. This lengthy period of inaction is somewhat surprising in light of the significant attention recently earned by high-frequency trading, in which informed trades and their price impact are expected to occur in milliseconds.

The informed trading analyzed in our context is distinct, however, from high-frequency trading. There are at least two possible explanations for both the notable intercept and the period of inaction we document in Figure 5. First, recent theoretical work by Foucault et al. (2015) suggests that, in the very short term, an informed speculator will trade in the direction in which he expects other traders who receive the same signal to trade – and then switch in the longer term to the direction suggested by his private assessment of the information. In our setting, a PDS subscriber who receives a filing early will trade immediately in the direction in which he expects other subscribers to trade, based upon whether the filing most likley represents positive or negative news. After that, the speculator will require time to produce, and then trade on, his private interpretation of the filing. While the filing is received by all subscribers, the subscribers' interpretations of the filing may differ, resulting in the production of additional private information (Kandel and Pearson (1995)). And indeed we document that it takes time – minutes, not seconds – for even sophisticated speculators to process new information about the fundamental value of a firm, which is distinct from an information advantage produced from the knowledge of order flows.[13]

[13]This possibility explains the finding of Rogers et al. (2014) that early informed traders react relatively quickly to information contained in Form 4's, the only securities filing included in that study. Form 4 essentially reveals the order flow produced by insider trading. The direction of the trades described in a Form 4 can be extracted and interpreted instantly. By contrast, assessing the nature of information disclosed

An alternative explanation for the relatively lengthy period of inaction that we document is that market makers may take as long as 1–2 minutes to detect informed trades. This is a plausible interpretation in light of the fact that a great majority (95%) of the filings in our sample are unscheduled. Hence, it is difficult for market makers to instantly assess the order flow from the early informed produced by the filings we study. A common trading strategy for the privately informed, as modeled by Obizhaeva and Wang (2006), is to immediately clear existing favorable outstanding orders – thus causing a small, instant price impact – and then to trade "patiently" and opportunistically in the next minute or two without causing additional price impact, before resorting to more aggressive trading when the private window is expected to end.

Our evidence provides support for both hypotheses. We retrieve all trades for the companies in our sample from TAQ and count the number of trades in each company's stock at the per-second frequency during the private window. Using the unbalanced panel, we run the following nonparametric regression using the standard kernel method:

$$\#Trades_{i,\tau} = f(\tau - t_1) + \epsilon_{i,\tau}, \text{for all } \tau \leq t_2. \tag{4}$$

The nonparametric relation, $f(.)$, between trading intensity (as measured by $\#Trades$) at each time point τ using the private window and time since the arrival of private information $(\tau - t)$ is plotted in Figure 6. Also shown in the chart is a benchmark level of trading intensity, providing a counterfactual level of trading activity for each filing. The benchmark level is calculated as the number of trades during a random second during a random non-event day (that is, a day on which the firm does not make a securities filing), averaged over all of the companies in the sample. Figure 6 shows that the modeled trading volume during the FTP-public delay reaches some ten times the normal trading volume in

in a Form 8-K – which relates to the firm's fundamental value – takes more time.

the first second after t_1. Trading volume then gradually declines during the private window, but always stays significantly higher than the normal volume. Therefore, our evidence shows that some informed trading takes place instantly – but it takes several minutes for privately informed traders to fully process the signal, and for their informed trading to be detected and reflected in market prices.

[Insert Figure 6 here.]

Second, the process of impounding private information into stock prices seems to be largely complete by the 5th or 6th minute after the privately informed receive both positive and negative news. (Though the scant data density around that range does not allow us to draw this conclusion with sufficient statistical confidence.) Delays beyond five minutes are uncommon and likely unexpected. As such, the informed may trade strategically such that the full price impact is realized during the first few minutes after they receive the information, making additional trades relatively unprofitable. Section 3.2.2 analyzes such strategic trading in more detail.

3.2. Information Dissemination

3.2.1. Information dissemination and length of delay

Having established the trading profitability of the advantage enjoyed by the early informed, we now turn our attention to the speed at which stock prices incorporate private information. We use the abnormal returns during the (t_1, t_3) window ($AR_i(t_1, d_1)$ or $AR_i(t_1, t_2 + 10\,\text{min})$) to capture the information content of a filing. The longer time window allows adequate time for the market to digest the new information, while the shorter window prevents other events from confounding the effect associated with the particular filing under study. Therefore, consistency across the results produced by both measures will give us more confidence.

To set the stage, we closely follow the setup and notations of Kyle (1985). We assume that the early informed observe private information at time $t = 0$, and the information is publicly revealed in time $t = 1$. Thus the early informed essentially observes v, the ex post value conditional on the private information. To the outsiders, at each point of time $0 < t < 1$, v is a random variable normally distributed with mean $p(t)$ and variance $\Sigma(t)$. The volume of noise trades, $u(t)$, is distributed with mean zero and variance σ_u^2. The quantity traded by the insider is $x(t)$. The model is characterized by a linear trading rule by the early informed $dx(t) = \beta(t)[vp(t)]dt$, and a linear pricing rule by the market maker $dp(t) = \lambda(t)[dx(t) + du(t)]$, where $\lambda(t)$ is the price impact or the inverse of market depth. A key insight from Kyle (1985) is that the early informed, if acting monopolistically and strategically, will trade in a way such that the price impact of their trading is constant over time. More importantly, Kyle (1985) shows that the pace at which the private information is disseminated via trading, as characterized by $\Sigma^{'}(t)/\Sigma(t)$, is a function of only time, and not a function of the ex ante variance $\Sigma(0)$ (i.e., the value of the private information) or market depth $\lambda(t)$ (which is a function of ex ante variance as well as the volume of noise trading). In fact, in the model, the pace of information dissemination follows a simple rule that $\Sigma(t)/\Sigma(0)$ is a constant linear function of time, altogether unaffected by other parameters representing market conditions.

Empirically, we use $AR_i(t_1, t_2)/AR_i(t_1, t_3)$, the percentage of total abnormal returns that occur during the private window, as a proxy for information dissemination. To ensure that the ratio of returns is well defined and that the filings under study contain a meaningful level of information content, we restrict the sample to filings for which $AR_i(t_1, t_3)$ is at least 0.5% in either direction. Setting t_3 to be $t_2 + 10\,\text{min}$ or d_1, 72.4% or 53.6% of the observations have positive values of $AR_i(t_1, t_2)/AR_i(t_1, t_3)$, respectively. Assuming that the market correctly assesses at least the directional change in the firm value based on the new SEC filing by t_3, then a negative value of $AR_i(t_1, t_2)/AR_i(t_1, t_3)$ indicates that informed trading, if it exists, does not sufficiently overcome noise trades to have a price impact; in other words, noise, rather than information, drives the stock prices during the private window. Our default specification thus retains the negative values of $AR_i(t_1, t_2)/AR_i(t_1, t_3)$, effectively interpreting noise as "negative information." An alternative method is to censor the negative values of the ratio as zero by treating noise as simply "non-information." Both specifications produce qualitatively similar results but the method we utilized has greater statistical power.

To summarize, we run the following linear regression model:

$$\begin{aligned}\frac{AR_i(t_1, t_2)}{AR_i(t_1, t_3)} =& \beta Delay_i + \vec{\mu} StockChar_i \cdot Delay_i + \vec{\eta} StockChar_i \\ &+ \vec{\lambda} Filing\,type_i + \alpha_t + \epsilon_i.\end{aligned} \tag{5}$$

In addition to the direct relation between information dissemination and the length of delay, (5) further examines the interactive relations with respect to stock characteristics which serve as proxies for the key parameters in the Kyle (1985) model. More specifically, we use the idiosyncratic volatility of the stock as a proxy for the ex ante variance of the stock Σ_0 , and we use market capitalization decile rank and the Amihud (2002) illiquidity measure as a proxy for market depth λ. Table 4 reports the results.

[Insert Table 4 here.]

Panel A of Table 4 offers an overview of how quickly the informational content of a particular filing (proxied for using $AR(t_1, t_3)$) is impounded into the stock price during the window when the information remains private. The independent variables are the same as in Table 3, where the key variable of interest is *Delay*, or the duration of time when information remains private. As a percentage of the total return from t_1 to d_1, every 100 second delay is associated with a 2.8–2.9 percentage point increase in private information dissemination, and the speed increases to 10.2–12.2 percentage points if we shrink the end point to $t_2 + 10\,\text{min}$ – a period during which the SEC filing is more likely to be the dominant information event. All of these coefficients are highly statistically significant at the 1% level.

The abnormal returns realized during the private window do not get close to 100% of the total (t_1, t_3) returns because $AR_i(t_1, t_3)$ is a noisy proxy for returns attributable to the new information in the filing, or $(v - p_0)/p_0$ in the Kyle (1985) model.

Panel B delves into more detail in the cross-sectional variation to explore the effects of the key parameters in the standard informed trading model. More specifically, in Panel B we examine whether the pace of information dissemination over the random delay is affected by the ex ante variance of the stock (proxied by $IdioVolatility$) and market liquidity (proxied by $MVDecile$ and $Illiquidity$). Hence the regressors of key interest are the interaction terms between $Delay$ and the various proxies. The results indicate that the pace of private information dissemination is stable with varying ex ante price variation as well as market depth. The coefficients of $Delay \cdot IdioVolatility$, $Delay \cdot MVDecile$, and $Delay \cdot Illiquidity$ are overall far from being statistically significant; and their economic magnitude also tends to be insignificant. Using $t_3 = d_1$ as an example, both $Delay \cdot IdioVolatility$ and $Delay \cdot MVDecile$ switch sign from the specification where each of the proxies serves as the only interactive variable to $Delay$ to the specification where all interactions are controlled for, suggesting the directional impact of idiosyncratic volatility and market capitalization is unclear. Stock illiquidity seems to accelerate information revelation, but the magnitude is small given that the coefficient should be multiplied by 0.125 to obtain the effect of a one standard deviation increase in the $Illiquidity$ measure.

Interestingly, the coefficient on $Delay \cdot After\ hours$ turns out to be significant, both statistically (at the 5% level) and economically. Column (4) of Table 4 Panel B indicates that about 1.1% of the total (t_1, d_1) abnormal returns are realized for every 100 seconds' delay during regular exchange trading hours (9:30am–4:00pm), but this rate increases to 7.8% after hours – quite a dramatic increase. The relative rate of information dissemination after hours is lower in the specification where $t_3 = t_2 + 10\,\text{min}$, and the coefficient is not statistically significant, but it remains remarkable in magnitude, as the dissemination rate per 100 seconds increases from 7.8% during market hours to 17.5% after hours. This new empirical evidence corroborates Barclay and Hendershott's (2004) finding that there is greater adverse selection during after-hours trading.

We thus offer the first study to quantify the relation between private information dissemination and the key parameters in the standard theoretical model. Such estimations have not been available to researchers precisely because the accurate arrival time of private information is, by definition, not observable to researchers – except in the rare case we are analyzing.

3.2.2. Strategic trading and predicted vs. residual delay

As in the setting of Koudijs (2014a), the speed at which early informed speculators trade on their private information depends on the expected duration of the private window. In Koudijs (2014a), the duration has exogenous variation – that is, three centuries ago, weather affected the journey by boats carrying newsletters across the Atlantic. In our setting, the private window has a random stopping time depending on traffic on the EDGAR server. While speculators in our sample could form some expectation about the duration of their private window – for which the single most powerful predictor is the time of the day for t_1 (see Figure 3) – the expectation is quite coarse, leaving a large residual variation in the form of an unexpected delay.

As an illustration, consider the following hypothetical example. Suppose a PDS subscriber receives a newsworthy SEC filing at 9:00am. At that time of the day, the expected delay is short (around 40 seconds). The speculator should trade as aggressively as possible and will probably reveal her private signal quite promptly. If, however, the actual delay were much longer at 200 seconds, the "unexpected" part of the delay (in this case, 160 seconds) is likely to be a wasted opportunity, because the private signal will have been revealed prematurely compared to an optimized strategy with a known delay of 200 seconds. By contrast, consider a scenario where private information arrives at around

4:00pm, when the expected delay is expected to be more than 200 seconds. In that case, a strategic speculator should trade smoothly in small quantities. If, however, the public release occurs much faster than usual and ends the private window after a mere 60 seconds, then the "residual" delay (140 seconds) would not contribute additional private information dissemination because the process was cut short. In both cases, the prediction is such that $\frac{AR_i(t_1,t_2)}{AR_i(t_1,t_3)}$ should bear a much stronger relation to the *expected* delay that traders predict will exist than to the unexpected, or residual, delay we actually observe.

Table 5 performs this test. Here the regressions are the same as in Table 4, except that the key independent variable *Delay* is replaced by two variables, *Predicted delay* and *Residual delay*. *Predicted delay* is the average delay for the hourly bin in which time t_1 of the i-th event falls. *Residual delay* is the difference between *Delay* and *Predicted delay*. Under all of our specifications, the statistical significance is higher for the coefficients on *Predicted delay* than *Residual delay*, as the former has more cross-sectional variation.

[Insert Table 5 here.]

Panel A reports results from the "modest" news sample – that is, cases in which $|AR_i(t_1, t_3)| > 0.5\%$. Indeed, we find that the coefficients on *Expected delay* are about 4-6 times as large as those on *Residual delay* across all three specifications for $t_3 = d_1$. An F-test on the difference between these coefficients indicates that the pairwise difference is significant at the 1% level in these specifications as well. If we use a shorter window, $t_3 = t_2 + 10\,\text{min}$, to record the stock price that incorporates the public information, the ratio of the two coefficients, around 2.0–2.5, is lower but substantively above unit, in which case the difference between the two coefficients is marginally significant (at the 10% level) in two out of the three specifications.

The "extreme" news sample ($|AR_i(t_1, d_1)| > 2\%$ or $|AR_i(t_1, t_2{+}10\,\text{min})| > 1\%$) provides similar results. The sample shrinks but both time windows (t_1, t_3) produce coefficients on *Predicted delay* that are notably larger than those on *Residual delay*, with ratios similar to those in Panel A except the last column where estimation with daily fixed effects on a small sample becomes unreliable. The F-tests for the difference in the two coefficients remain significant at the 1% level for $t_3 = d_1$, but are insignificant for $t_3 = t_2 + 10\,\text{min}$ though the relative magnitude of the coefficients remain informative.

Overall, the results in Table 5 suggest that the early informed trade aggressively based on the time advantage they expect to have – rather than the advantage they actually enjoy. These results echo Koudijs' (2014a) finding that the co-movement between the London and Amsterdam exchanges was significantly higher when the next boat was expected to arrive sooner (depending on the wind and weather conditions), which implies that the speed of information dissemination in Amsterdam depended on how long insiders expected it would take for their private signal to become public.

4. Overreaction to Stale News at Public Release

During our sample period, public investors were likely not aware of the fact that some investors were gaining access to SEC filings before the public release of that information. In fact, the magnitude of the public's surprise was apparent in light of the outrage expressed in the media and by lawmakers upon the revelation of the dissemination delay. As such, investors were most likely not aware that information made available on EDGAR was already stale by the time the filings reached the SEC's public website. The combination of the investors' late-informed status together with an ignorance of that status predicts that public investors may overreact to the news contained in public releases even if those investors are otherwise fully rational. To the extent that the length of the information advantage obtained by the early informed is positively associated with the staleness of news at public release (as shown in Tables 3 to 5), it should also be positively associated with the extent of investors' overreaction to that information.

It is worth noting that overreaction to stale news in our setting is of a different nature from that in Huberman and Regev (2001) and Tetlock (2011). In those two studies, investors treat all information as news without differentiating "printed" from "reprinted" news, i.e., news with either full or partial content that was already described in earlier releases. Thus, the investors in those studies are interpreted to be naïve or unsophisticated in assessing the incremental content of public news. In our setting, investors – even many sophisticated ones – were likely unaware of the possibility that some traders could front-run on filings submitted to the SEC – an agency whose stated mission is to create a level playing field for all market participants.

Following Tetlock (2011), overreaction to stale news can be tested by showing whether there is return reversal in the "steady state" after the first trading period following the public news release, i.e., (t_2, t_3) as previously defined. We now introduce another time point, t_4, to proxy for the "steady state." We set $t_4 = d_5$, the market close five days after the public release, based on Tetlock's (2011) finding that it takes up to five days for market overreactions to reverse. Figure 2 displays and explains the relation among all the time points, t_1 to t_4. We then examine whether part of $AR_i(t_2, t_3)$ is reversed during the period (t_3, t_4), or whether $AR_i(t_2, t_3)$ negatively predicts (t_3, t_4).

Figure 5, and our discussion in Section 3.1.2, show that there is little price reaction to private information during the first 100 seconds of the FTP-public delay. Thus, the subsample of filings with delays of 100 seconds or less should serve as a benchmark for the relation between $AR_i(t_2, t_3)$ and (t_3, t_4). If stock prices on average do not incorporate the information possessed by the early informed during these first 100 seconds of the FTP-public delay, we should find no "overreaction" by the late informed – because, in essence, in these cases the news remains "fresh" at the time of public release (t_2). We thus perform the following regression on the subsample of files with short delays:

$$AR_i(t_3, t_4) = \beta AR_i(t_2, t_3) + \vec{\lambda} Filingtype_i + \alpha_t + \epsilon_i. \tag{6}$$

The results, reported in Panel A of Table 6, show that when the delay is too short for the private information to be impounded into the stock price – that is, when the delay is 100 seconds or less – there is no overreaction to the information afterwards. In fact, the coefficients on $AR_i(t_2, t_3)$ are all positive but statistically insignificant.

[Insert Table 6 here.]

This relationship is quite different, however, when we turn our attention to the sample of filings with longer delays – that is, FTP-public delays of more than 100 seconds. Panel B of Table 6 shows that the coefficients of $AR_i(t_2, t_3)$ are uniformly negative across all specifications in this sample. Approximately 27%–31% of the returns during the 10-minute window immediately following the public release of the filings are reversed during the next 4–5 days, and the overreaction is significant (at the 5% and 10% levels). Using the day's market close as the end of the first public trading period, 22%–23% of the returns during this period are reversed during the four-day period that follows. The reversals are barely significant on their own, but the differences between the β coefficients on $AR_i(t_2, t_3)$ in (6) between the short-delay and long-delay subsamples are all significant at the 5% level. Moreover, in untabulated results we show that the relation between overreaction and delay is not affected by stock characteristics such as market capitalization and trading liquidity.

Figure 7 provides a visualization of the nature of the market's overreaction when the delay is long enough for the early informed traders' private information to be impounded into stock prices. Conditional on *Delay* being greater than 100 seconds, we plot the cumulative abnormal buy-and-hold returns from the arrival of the private information (t_1) to the market close of the fifth trading day afterwards (d_5), with intermediate time points of interest, t_2, $t_2 + 10\,\text{min}$, d_1, ..., d_4 highlighted separately for positive and negative news classified by the sign of $AR_i(t_1, d_1)$. Panels A and B of Figure 7 plot the full sample separated by positive and negative news, while Panels C and D restrict the subsample to "extreme" news, defined as filings for which the ex post $AR_i(t_1, d_1)$ is greater than 2% in absolute magnitude.

[Insert Figure 7 here.]

Interestingly, the figures reveal that overreaction is present only for positive news but not for negative news. There are two potential explanations for this asymmetry. First, there could be a baseline asymmetry in reaction to favorable and unfavorable (non-stale) news about the firm – that is, the "bad news travels slowly" phenomenon described in Hong et al. (2000), especially when the source of the negative information is the firm itself, which reveals this information via its regulatory filings. Second, this effect could be further reinforced by short sale constraints which reduce the adjustment speed of stock prices to private information about bad news (Diamond and Verracchia (1987)).

We confirm this relation in our sample. In untabulated analysis, we separate the regressions in Panel A of Table 6 into positive and negative news by the sign of $AR_i(t_1, t_3)$. We find that, for the short-delay (fewer than 100 seconds) subsample of filings, the coefficients on $AR_i(t_2, t_3)$ are very close to zero both economically and statistically for positive news, but the same coefficients are substantial (0.19–0.24) for the negative news subsample and are significant at the 10% level. Therefore, it seems that the market reacts properly to positive news but underreacts to negative news when the news is not stale. Such an asymmetry is not peculiar to our sample. In fact, Heston and Sinha (2014), using a comprehensive sample of news stories, document that stock returns react to positive news quickly but negative stories have a long-delayed reaction.

In sum, our evidence shows that public investors overreacted to SEC filings containing news on the day of the public release because these investors were not aware that the news was already stale for filings for which there was a significant delay. The extent of the overreaction is relative to the level of over- or under-reaction, as manifested in the intertemporal return relations from the initial public trading period to a steady state. The absence of a relative overreaction when the delay was minimal indicates that investors were not irrational but only ignorant – and rightly so – about the fact that the news was already stale when it was publicly released. The evidence shows that the early release of SEC filings to a small group of investors hurt the investing public, inflicting more damage than would have been incurred if PDS subscribers' time advantage had been public knowledge.

5. Conclusion

Using rare data from an unusual episode in which SEC filings containing market-moving information were disseminated to a small group of investors before the public release of that information, we examine a quasi-natural experiment that provides a direct test of the process through which private information is impounded into stock prices. The study serves as a counterpart to Koudijs's (2014a) analysis of insider trading during the eighteenth century, although we benefit from the privilege of more granular trading information afforded by modern data.

Contrary to the common public intuition about how quickly "fast" traders can act on new information, we find that it takes time – minutes, not seconds – for informed investors to impound fundamental information into public-company stock prices. As one might expect, informed investors convey more information into stock prices through their trading when the delay between private and public revelation of the information is longer. More importantly, information dissemination is much more strongly correlated with the predicted length of the delay rather than the actual delay, consistent with the notion that informed investors trade strategically, evening out the price impact of their trading. Finally, we show that public investors overreacted to positive news contained in SEC filings, because they were unaware that the information was stale by the time it arrived on the SEC's EDGAR website. Our study contributes to the relatively scant empirical literature on the critical process through which private information is incorporated into stock prices.

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Figure 1. PDS-EDGAR Delay Time Heatmap: August 2014 to April 2015

The heatmap monitors the percentage of filings released to PDS before EDDAR from August 2014 to April 2015. The real-time monitoring can be viewed at: http://crown.law.columbia.edu/, which website is maintained by two of the authors (Jackson and Mitts) with support from the Ira M. Millstein Center for Global Markets and Corporate Ownership.

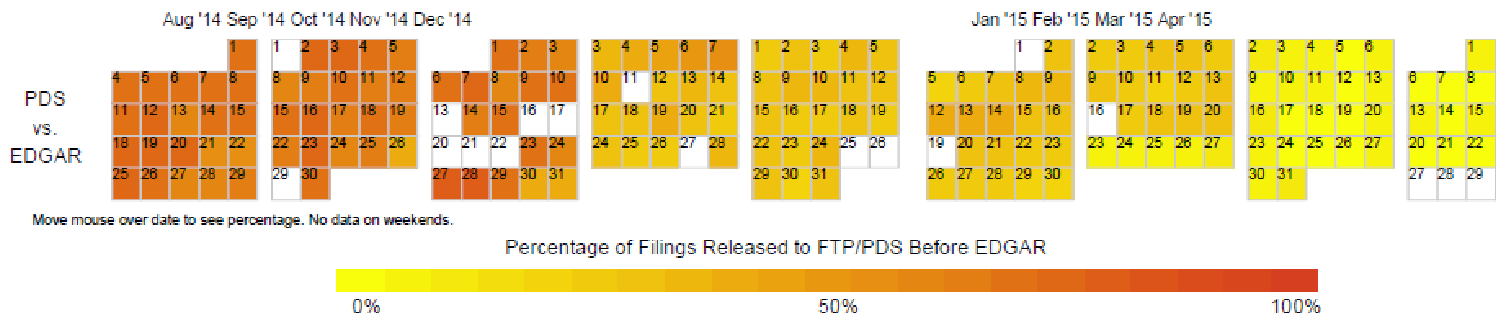
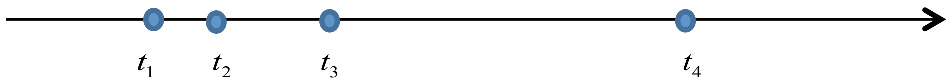


Figure 2. Timeline of Key Events



t_1: An SEC filing becomes accessible to the early informed on the Public Dissemination Service (PDS).

t_2: The same SEC filing becomes publicly accessible on EDGAR.

t_3: Ten minutes after t_2 (i.e., $t_2 +$ 10 min), or the market close on the day following t_2 (i.e., d_1). The interval (t_2, t_3) is a proxy for the period during which the public investors trade on the information revealed by the SEC filing.

t_4: The market close on the 5th day following t_2 (i.e., d_5), a proxy for the time by which the market corrects any potential overreaction to news.

Figure 3. Average FTP-Public Delay Time and Filing Intensity throughout the Trading Day

On the left vertical axis, this figure shows the average delay in the public release of all filings with the SEC during the sample period of June 25, 2014 to October 15, 2014 (excluding July 15, 2014) by hourly intervals. The delay is calculated as the difference in time, in seconds, between the SEC's file transfer protocol (FTP) timestamp for the filing—a proxy for the actual time that filings reach the subscribers to the Public Dissemination Service (PDS)—and the SEC's Electronic Data Gathering, Analysis, and Retrieval System (EDGAR) timestamp (the actual time when filings are released to the public). On the right vertical axis, the figure shows the percentage of all 42,619 filings, or of the 2,566 filings with at least one trade during the private window of (t_1, t_2), that occur during each hour.

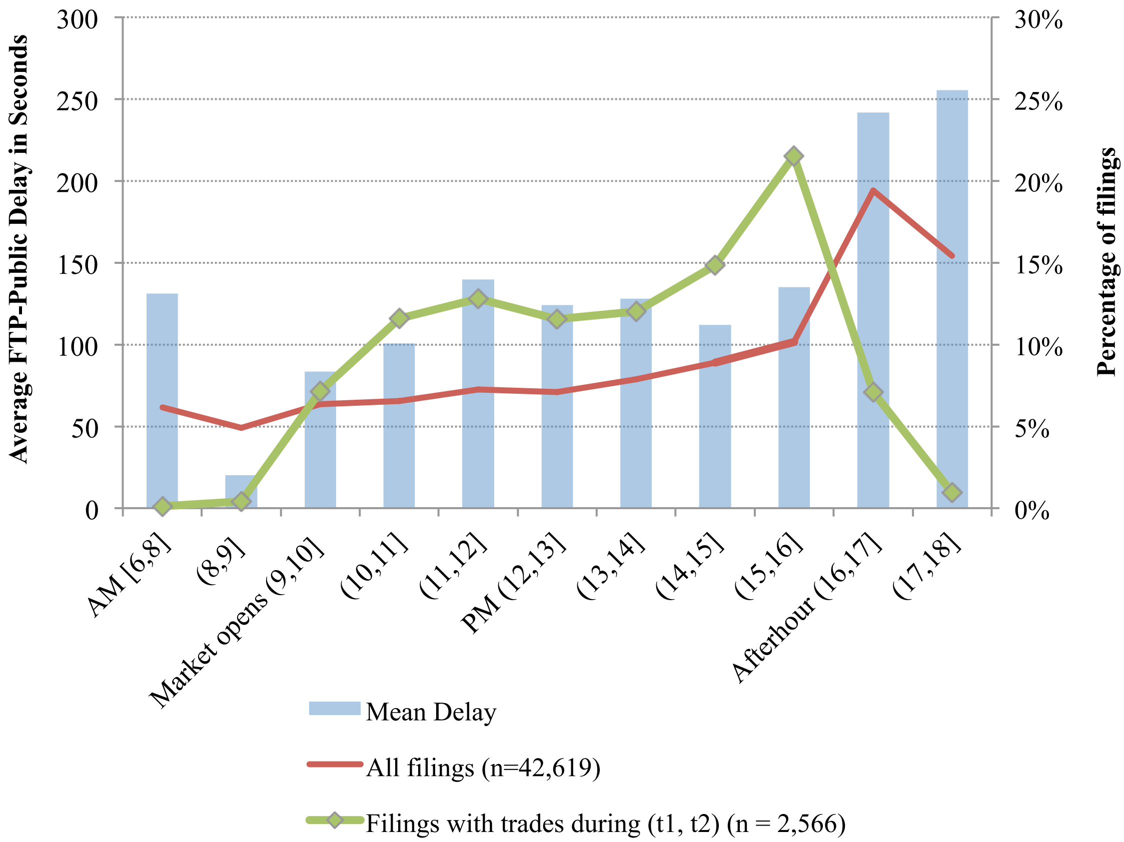


Figure 4. Histogram of Abnormal Returns during the FTP-Public Delay

This figure plots the histogram of abnormal returns during the FTP-public delay (as defined in Figure 2). The abnormal returns are calculated as the difference between the stock returns of the companies making the filing and the returns of the SPY, the most liquidly traded exchange-traded-fund (ETF) tracking the S&P 500 index. The dotted graph represents the hypothetical histogram from a normal distribution.

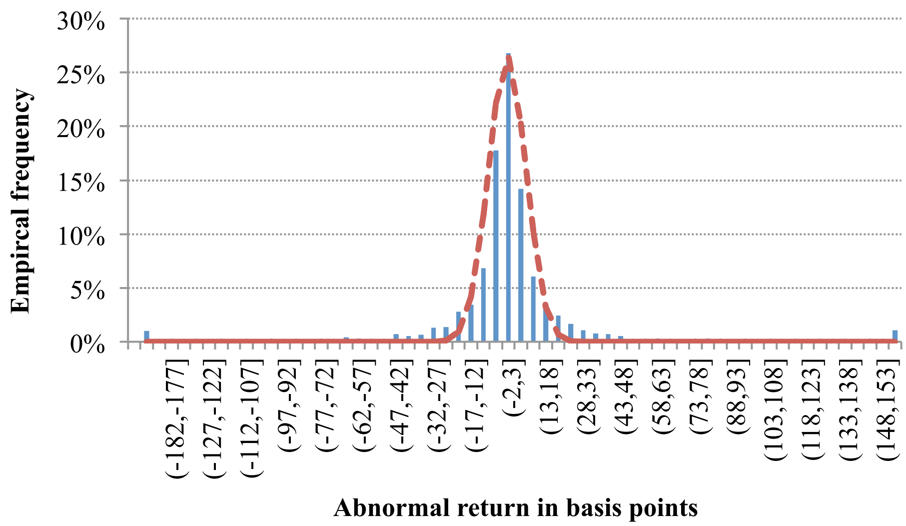
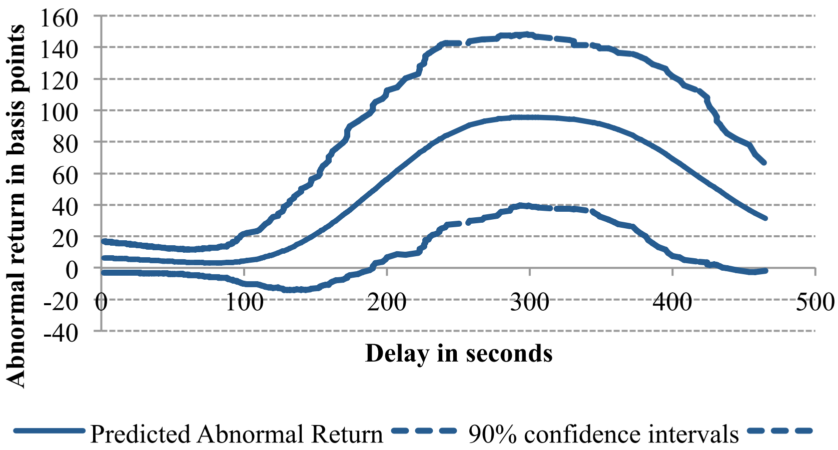


Figure 5. Kernel Regression of Abnormal Return vs. the FTP-Public Delay

This figure plots the kernel regression of the abnormal return, $AR(t_1,d_1)$, against the length of the FTP-public delay (as defined in Figure 2), conditional on extreme news (i.e., $AR(t_1,d_1)$ is greater than 2% in absolute magnitude). All kernel regressions adopt the Gaussian kernel with bandwidth of 50. The dotted lines represent 90% confidence intervals, calculated by bootstrapping with replacement.

Panel A: Extreme Positive news: $AR(t_1,d_1) > 2\%$



Panel B: Extreme negative news: $AR(t_1,d_1) < -2\ \%$

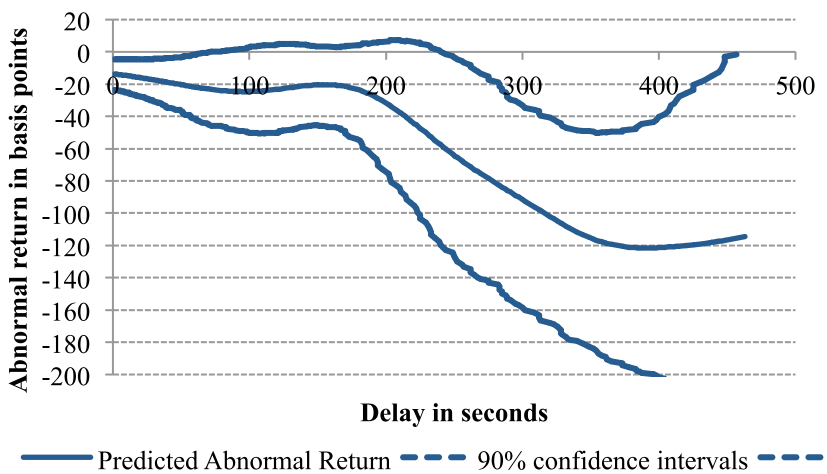


Figure 6. Trading Volume during the Private Window

This figure plots a kernel regression of the number of trades at the second-level interval during the FTP-public delay. The regression adopts the Gaussian kernel with a bandwidth of 6.35 (which minimizes the conditional-weighted, mean-integrated squared error). The dotted lines represent the 95% confidence intervals based on local polynomial approximations. The flat "Benchmark" line shows the average number of trades per second outside the event windows for the same firms. The average is computed as follows: for each filing in the dataset, a random date in 2013 when the firm did not make a securities filing was chosen. Then, for each filing, one second was randomly sampled from this random date and the number of trades present in the TAQ data on that date was recorded.

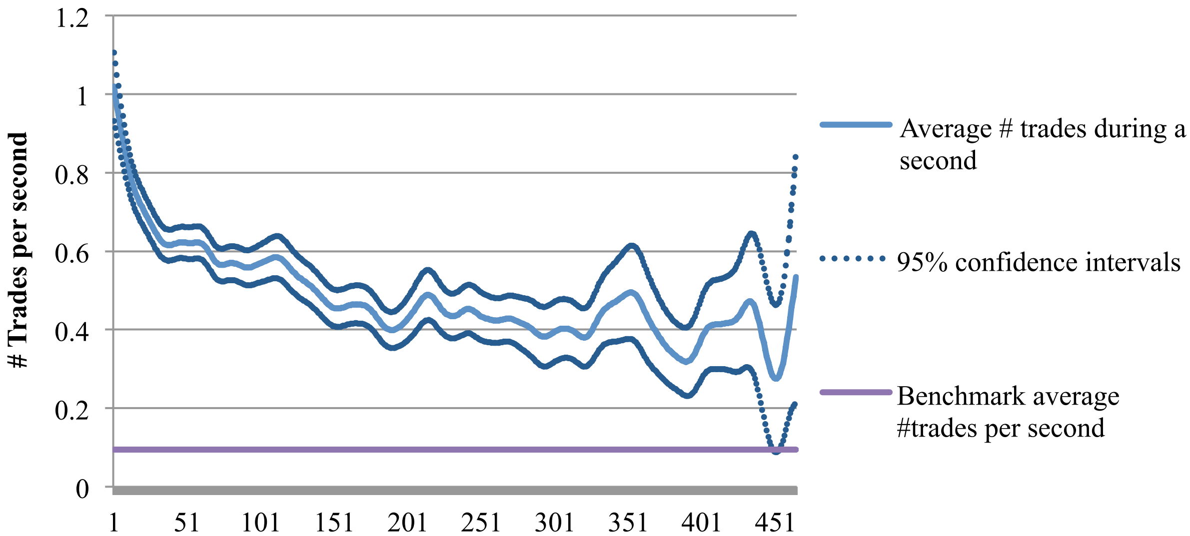
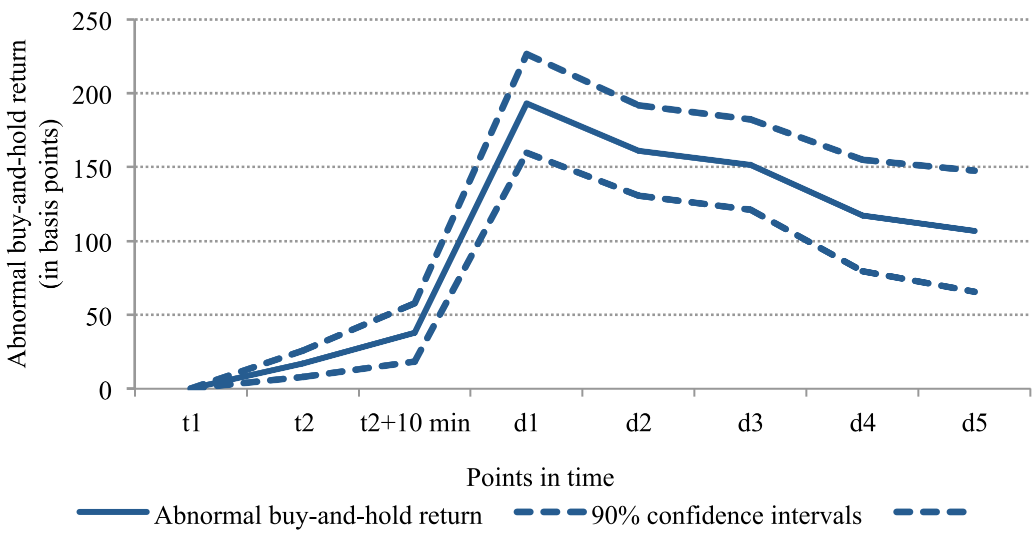


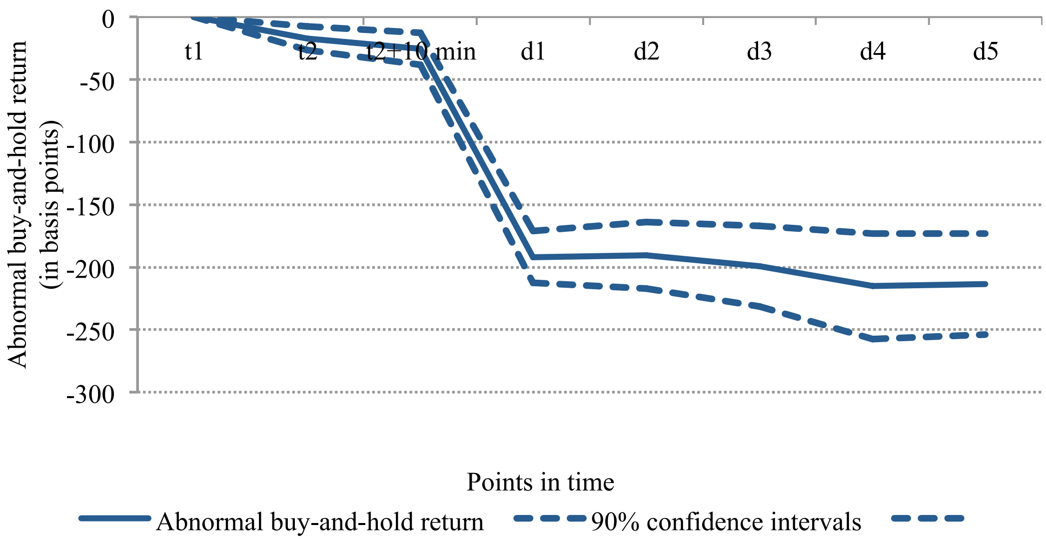
Figure 7. Overreaction: Abnormal Buy-and-Hold Return over Time

This figure plots the abnormal buy-and-hold returns from the arrival of private information to the market close of the 5th day post information. The time points examined (t_1, t_2, t_2+10 min, d_1,…, d_5) are defined and explained in Figure 1. The samples in all panels are restricted to observations in which the FTP-EDGAR delay exceeds 100 seconds. Panels A and B use the sample of all news, while Panels C and D focuses on the subsamples of "extreme" news defined as $|AR(t_1,d_1)| > 2$ %. Panels A and C examine positive news and Panels B and D examine negative news. Positive/negative news is classified by the sign of $AR(t_1,d_1)$. The dotted lines represent the 90% confidence intervals based on the *t*-statistics of the average returns.

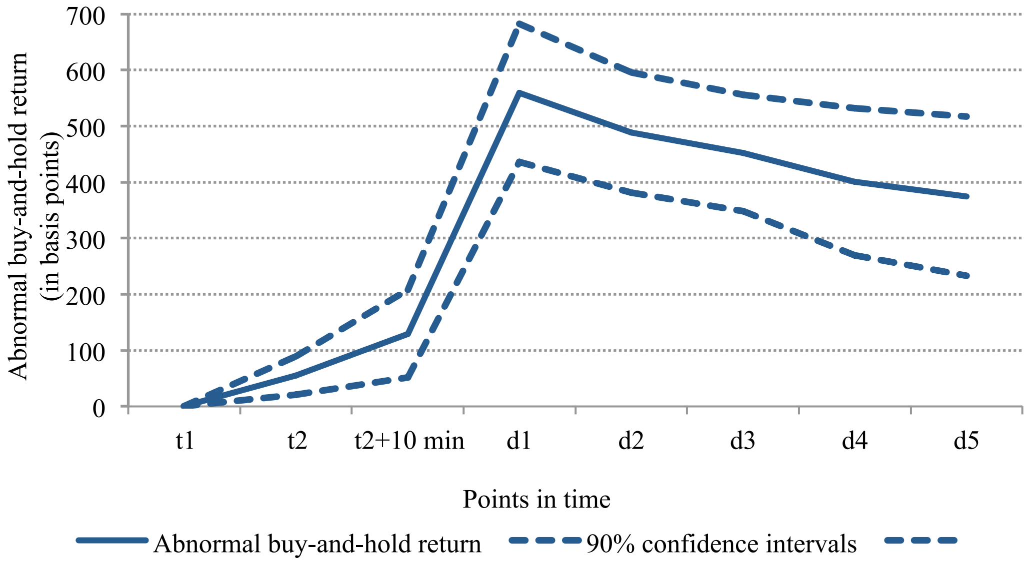
Panel A. Full sample/Positive news



Panel B. Full sample/Negative news



Panel C. Extreme positive news: $AR(t_1,d_1) > 2\%$



Panel D. Extreme negative news: $AR(t_1,d_1) < -2\ \%$

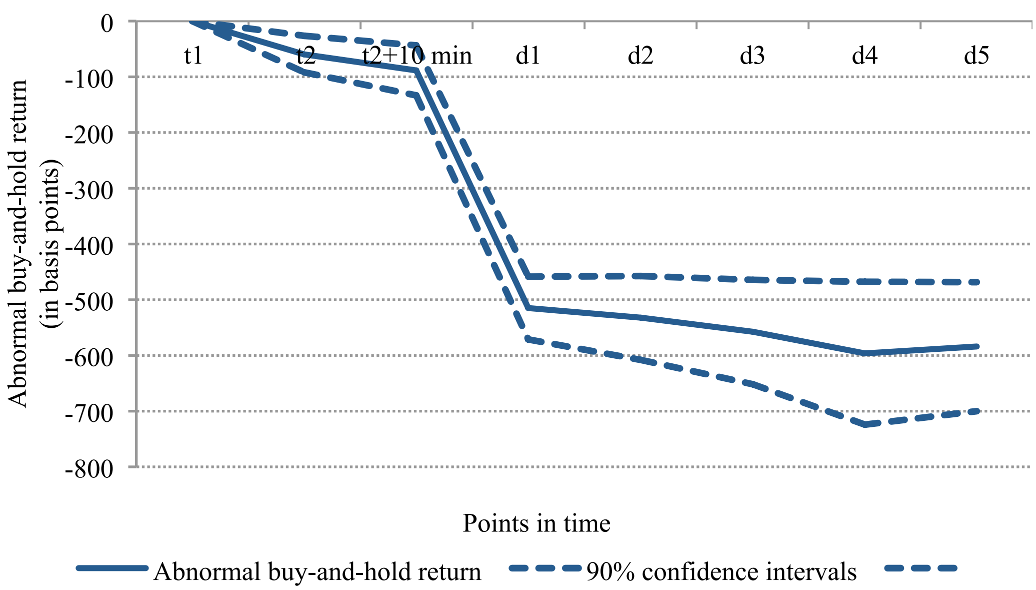


Table 1. Distribution of the FTP-Public Delay

This table reports summary statistics (mean, standard deviation, and the various percentile values) describing the delay in the public release of all filings by public companies during the sample period of June 25, 2014 to October 15, 2014 (excluding July 15, 2014). The delay is calculated as the difference in time, in seconds, between the posting of the filing to the SEC's file transfer protocol (FTP) server (a proxy for the actual time that a filing reaches subscribers to the Public Dissemination Service (PDS)) and the posting of that filing to the SEC's Electronic Data Gathering, Analysis, and Retrieval System (EDGAR) (the actual time at which the filing is publicly released). Summary statistics for the full sample, as well as for the top three filing types—Form 8K, Form 4, and Schedule 13D—are reported. Form 8-K provides timely disclosure of material corporate events, Form 4 discloses transactions in the company's stock by insiders, and Schedule 13D discloses 5% or greater beneficial ownership with an intention to influence corporate control or policies, within 10 days after the investor crosses the 5% threshold.

	All Files	**Form 8K** (News release)	**Form 4** (Insider trading)	**Schedule 13D** (Activist block formation)
# observations	42,619	7,227	22,219	517
10th percentile	4	3	4	4.6
25th percentile	7	7	7	12
Median	26	33	24	59
75 percentile	172	203	159	231
90 percentile	466	471.4	451	498
Mean	219.52	180.66	233.13	191.21
Standard Deviation	3242.28	425.56	3995.73	375.29
Truncated mean	130.63	145.94	122.67	94.23
Truncated standard deviation	128.80	137.40	125.69	131.10

Table 2. Determinants of the Occurrence of Trades during the Private Window

Panel A reports summary statistics for the principal variables of interest for our initial and final samples of filings. The initial sample includes all 38,352 filings by public companies during our sample period for which the FTP-public delay was 466 seconds (the 90^{th} percentile) or less. The final sample includes all 2,523 filings with at least one trade during the private window. The unconditional probability of a filing being included in our final sample is 6.58%. *Delay* is the FTP-public delay in 100-second units. *After hours* is a dummy variable equal to one if the filing time is before 9:30am or after 4:00pm. *MV Decile* is a numerical value between 1 (smallest) to 10 (largest) for the market capitalization decile ranking as of June 30, 2014. *Illiquidity* is the Amihud (2002) illiquidity measure, estimated as the semi-yearly average of $1000\sqrt{|\mathit{Return}|/(\text{Dollar Trading Volume})}$ from July 1, 2013 to June 30, 2014, using daily data. *Idio volatility* is the idiosyncratic volatility of an issuer's stock, estimated as the annualized volatility of return residuals from the Fama-French (1993) plus Carhart (1997) four-factor model using daily return data from July 1, 2013 to June 30, 2014. *Illiquidity* and *Idio volatility* are pre-winsorized at the 1% extremes. Finally, *Form 8K, Form 4,* and *Schedule 13D* are dummy variables for file types as defined in Table 1.

Panel B reports results from filing-level cross sectional logit regressions where the dependent variable is a dummy variable equal to one if a filing is included in our final sample. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A. Summary statistics

	Initial Sample (38,352 filings)					Final Sample (2,523 filings)				
	Mean	Std. Deviation	25th	Median	75th	Mean	Std. Deviation	25th	Median	75th
Delay	75.6	109.4	7	19	100	130.6	128.8	23	82	214
After hours	0.556	0.497	0	1	1	0.095	0.293	0	0	0
MV ($ million)	9618	26748	290	1274	5449	19547	39326	1026	4154	17398
MV decile	5.1	3.0	2	5	8	6.8	2.7	5	7	9
Illiquidity	0.140	0.222	0.017	0.047	0.163	0.057	0.125	0.009	0.018	0.048
Idio volatiltiy	0.310	0.217	0.162	0.242	0.379	0.261	0.184	0.144	0.199	0.303
Form 8K	0.169	0.375	0	0	0	0.222	0.416	0	0	0
Form 4	0.524	0.499	0	1	1	0.336	0.472	0	0	1
Schedule 13D	0.012	0.108	0	0	0	0.009	0.092	0	0	0

Panel B: Determinants of Occurrence of Trades during the Private Window

	(1)	(2)
Delay (100 seconds)	0.3739***	0.6280***
	(27.86)	(33.54)
After hours		-3.4045***
		(-45.76)
MV decile		-3.4045***
		(-45.76)
Illiquidity		-2.4253***
		(-6.49)
Idio volatiltiy		-2.4253***
		(-6.49)
Form 8K		0.5285***
		(8.43)
Form 4		-1.1561***
		(-20.73)
Schedule 13D		-0.3368
		(-1.25)
Constant	-3.0019***	-2.1552***
	(-114.73)	(-48.56)
Observations	38,352	34,917

Table 3. Abnormal Returns during the Private Window

In both Panel A and Panel B below, the dependent variable is $AR(t_1, t_2)$, the abnormal return during FTP-Public delay in basis points. In each panel the full sample is sorted into the"positive news" and "negative news" subsamples depending on the sign of $AR(t_1, t_3)$, the total abnormal return observed over a period concluding after the public revelation of the news. The key independent variable is *Delay*, the length of the FTP-public delay in seconds. Control variables include filing types and daily fixed effects. In Panel A, t_3 is set to be d_1, the market close on the day following the public release of the filing; in Panel B, t_3 is set to be $t_2 +$ 10 min, ten minutes after the public release of the filing. The t-statistics based on standard errors adjusted for heteroskedasticity are reported below the coefficients in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A: All News and $t_3 = d_1$

	(1)	(2)	(3)	(4)	(5)	(6)
	Positive News: $AR(t_1,d_1) > 0$			Negative News: $AR(t_1,d_1) < 0$		
Delay	0.0650***	0.0621***	0.0646***	-0.0857***	-0.0804***	-0.0846***
	(3.02)	(2.98)	(3.32)	(-2.68)	(-2.67)	(-2.55)
Form 8K		14.4765*	11.9615		-18.2928*	-18.1595*
(News release)		(1.67)	(1.57)		(-1.78)	(-1.72)
Form 4		-1.4707	1.3164		5.0554	-0.0833
(Insider trading)		(-0.41)	(0.36)		(1.27)	(-0.02)
Schedule 13D		3.3194	12.4766		-75.4596	-94.3357
(Activist block formation)		(0.13)	(0.50)		(-0.96)	(-1.14)
Constant	0.0638	-2.2882	-3.0518	1.8928	4.0464	6.4134
	(0.03)	(-0.81)	(-1.17)	(0.66)	(0.79)	(1.15)
Daily fixed effects	N	N	Y	N	N	Y
R-squared	0.010	0.015	0.153	0.011	0.021	0.086
Observations	1,208	1,208	1,208	1,315	1,315	1,315

Panel B: $t_3 = t_2 + 10$ min

	(1)	(2)	(3)	(4)	(5)	(6)
	Positive News: $AR(t_1,\ t_2{+}10\ \text{min}) > 0$			Negative News: $AR(t_1,\ t_2\ {+}10\ \text{min}) < 0$		
Delay	0.0723***	0.0708***	0.0780***	-0.0926***	-0.0861***	-0.0903***
	(3.16)	(3.19)	(3.41)	(-3.12)	(-3.13)	(-2.92)
Form 8K		15.8717*	14.2107*		-18.9438*	-20.2260*
(News release)		(1.78)	(1.81)		(-1.91)	(-1.93)
Form 4		-4.6449	-5.1760		8.0612**	2.5239
(Insider trading)		(-1.26)	(-0.99)		(2.14)	(0.61)
Schedule 13D		20.7098	23.6425		-45.0684	-50.4168
(Activist block formation)		(0.61)	(0.72)		(-1.09)	(-1.11)
Constant	4.2127**	2.2743	1.8388	-2.4910	-1.4153	1.3408
	(2.05)	(0.66)	(0.51)	(-0.94)	(-0.32)	(0.26)
Daily fixed effects	N	N	Y	N	N	Y
R-squared	0.011	0.020	0.096	0.014	0.026	0.099
Observations	1,232	1,232	1,232	1,328	1,328	1,328

Table 4. Information Dissemination and the FTP-Public Delay

The dependent variable in this table is % $AR(t_1,t_2)/AR(t_1, t_3)$, the proportion of total abnormal returns post-public trading that are realized during the private window (t_1,t_2) in percentage points. The sample includes all observations for which $|AR(t_1, t_3)|>0.005$ so that the ratio is well-defined. The timeline of events is defined in Figure 1. The key independent variable is *Delay*, the length of the FTP-public delay in seconds. Control variables include filing types and daily fixed effects. In Panel A, the sample includes "modest" news, defined as cases in which $AR(t_1, t_3)$ is greater than 0.5% in absolute magnitude. The sample in Panel B consists of "extreme" news, that is, cases in which $AR(t_1, t_3)$ is greater than 2% (or 1%) in absolute value. The first three columns of both panels set t_3 to be d_1, while the last three columns set t_3 to be t_2 + 10 min. The *t*-statistics based on standard errors adjusted for heteroskedasticity are reported below the coefficients in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A: Overview

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	% $AR(t_1,t_2)/AR(t_1, d_1)$			% $AR(t_1,t_2)/AR(t_1, t_2+10min)$		
Delay	0.0286***	0.0280***	0.0282***	0.1202***	0.1224***	0.1017***
	(3.65)	(3.61)	(4.13)	(4.27)	(4.20)	(4.42)
Form 8K		2.3803	1.5601		0.1836	-5.7905
(News release)		(1.18)	(0.76)		(0.02)	(-0.55)
Form 4		-0.5506	0.7156		-8.5014	-6.1352
(Insider trading)		(-0.38)	(0.46)		(-0.91)	(-0.58)
Schedule 13D		1.9370	1.6255		9.1250	2.3628
(Activist block formation)		(0.18)	(0.15)		(0.32)	(0.09)
Constant	-0.8694	-1.2570	15.8353	9.7482**	11.0906*	51.9748***
	(-1.11)	(-1.20)	(1.38)	(2.48)	(1.84)	(3.39)
Daily fixed effects	N	N	Y	N	N	Y
R-squared	0.015	0.017	0.072	0.056	0.059	0.228
Observations	1,694	1,694	1,694	424	424	424

Panel B: Effect of Strength of Signal and Market Depth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	% $AR(t_1, t_2)/AR(t_1, d_1)$					% $AR(t_1, t_2)/AR(t_1, t_2$+10min)				
Delay	0.0261***	0.0269***	0.0273***	0.0113*	0.0085*	0.1132***	0.1285***	0.1173***	0.0780***	0.0755***
	(3.54)	(3.32)	(3.52)	(1.92)	(1.84)	(3.46)	(3.13)	(3.93)	(4.06)	(2.83)
Delay · Idio Volatility	0.0515				-0.0149	0.0351				0.0368
	(1.53)				(-0.34)	(0.31)				(0.34)
Delay · MV Decile		-0.0017			0.0005		0.0064			0.0156
		(-0.54)			(0.16)		(0.51)			(0.95)
Delay · Illiquidity			0.0850		0.1307			0.0717		0.2123
			(1.12)		(1.59)			(0.27)		(0.64)
Delay · After hours				0.0662**	0.0720**				0.0968	0.0973
				(2.02)	(2.11)				(1.34)	(1.49)
Idio Volatility	-2.6893				-1.8918	-3.5742				-11.2306
	(-0.39)				(-0.23)	(-0.15)				(-0.52)
MV Decile		-0.0167			-0.2967		-1.4150			-3.5368
		(-0.04)			(-0.56)		(-0.86)			(-1.23)
Illiquidity			-3.2476		-7.1885			-8.3005		-32.4164
			(-0.24)		(-0.44)			(-0.17)		(-0.53)
After hours				0.8728	1.1029				-7.7765	-3.7159
				(0.18)	(0.20)				(-0.53)	(-0.26)
Constant	-0.7618	-0.8129	-0.8602	-0.3099	-0.1771	9.8166**	7.9333**	10.0649***	12.2946***	10.4560***
	(-1.07)	(-1.00)	(-1.11)	(-0.46)	(-0.28)	(2.47)	(2.12)	(2.79)	(3.83)	(2.95)
R-squared	0.021	0.016	0.019	0.047	0.065	0.055	0.057	0.056	0.067	0.075
Observations	1,649	1,694	1,694	1,694	1,649	412	424	424	424	412

Table 5. Information Dissemination and Strategic Trading

The dependent variable in this table is % $AR(t_1,t_2)/AR(t_1,\ t_3)$, the proportion of total abnormal returns post-public trading that are realized during the private window (t_1,t_2). The key independent variables are *Predicted delay* and *Residual delay*. *Predicted delay* is proxied for by the average delay for the hourly bin in which time t_1 of the i-th event falls. *Residual delay* is the difference between *Delay* and *Predicted delay*. Control variables include filing types and daily fixed effects. In Panel A, the sample includes "modest" news, defined as cases in which $AR(t_1,\ t_3)$ is greater than 0.5% in absolute magnitude. The sample in Panel B consists of "extreme" news, or cases in which $AR(t_1,\ t_3)$ is greater than 2% (or 1%) in absolute value. The first three columns of both panels set t_3 to be d_1, whereas the last three columns set t_3 to be t_2 + 10 min. The t-statistics based on standard errors adjusted for heteroskedasticity are reported below the coefficients in parentheses. The bottom of the table reports the F-test statistics as well as the associated p-value for the equality of the coefficients on *Predicted delay* and *Residual delay* . *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A: "Modest" news: $|\ AR(t_1,\ t_3)| > 0.5\%$

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	% $AR(t_1,t_2)/AR(t_1,\ d_1)$			% $AR(t_1,t_2)/AR(t_1,\ t_2$+10 min)		
Predicted Delay	0.1011***	0.0957***	0.0910***	0.1667***	0.1544***	0.1765***
	(4.04)	(3.96)	(3.95)	(2.99)	(2.81)	(3.22)
Residual Delay	0.0156***	0.0157***	0.0177***	0.0767***	0.0800***	0.0622***
	(2.68)	(2.70)	(3.02)	(3.78)	(3.87)	(2.89)
Form 8K		2.1154	1.8672		3.4304	-0.4281
(News release)		(1.18)	(1.09)		(0.52)	(-0.07)
Form 4		0.2489	1.2592		-3.5775	-7.5553
(Insider trading)		(0.20)	(0.87)		(-0.51)	(-0.91)
Schedule 13D		2.6050	2.2199		8.7550	-0.3492
(Activist block formation)		(0.25)	(0.21)		(0.31)	(-0.01)
Constant	-10.8808***	-10.7836***	5.8296	2.3686	3.4810	38.9511**
	(-3.45)	(-3.42)	(0.48)	(0.28)	(0.40)	(2.27)
Daily fixed effects	N	N	Y	N	N	Y

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	% $AR(t_1,t_2)/AR(t_1,\ d_1)$			% $AR(t_1,t_2)/AR(t_1,\ t_2$+10 min)		
R-squared	0.0277	0.0288	0.0869	0.0563	0.0586	0.2506
Observations	1,664	1,664	1,664	406	406	406
Test: Predicted Delay = Residual Delay						
F-statistics	25.6326***	21.1369***	16.1192***	2.7875*	1.6892	2.9691*
p-value	0.0000	0.0001	0.0001	0.0958	0.1944	0.0856

Panel B: "Extreme" news: $|\ AR(t_1,\ d_1)\ | > 2\%$ or $|\ AR(t_1,\ t_2{+}10\ \text{min})\ | > 1\%$

	(1)	(2)	(3)	(4)	(5)
Dependent variable		% $AR(t_1,t_2)/AR(t_1,\ d_1)$		% $AR(t_1,t_2)/AR(t_1,\ t_2{+}10\ \text{min})$	
Predicted Delay	0.0825***	0.0744***	0.1023***	0.1485**	0.1547**
	(2.84)	(2.80)	(3.75)	(2.31)	(2.51)
Residual Delay	0.0171**	0.0179**	0.0129*	0.0724***	0.0790***
	(2.35)	(2.51)	(1.84)	(2.64)	(2.82)
Form 8K		2.8092	3.5524*		-0.0808
(News release)		(1.51)	(1.67)		(-0.01)
Form 4		-0.8109	1.7575		-6.7896
(Insider trading)		(-0.51)	(0.90)		(-0.71)
Schedule 13D		15.0770	18.1851		33.2054
(Activist block formation)		(1.06)	(1.44)		(1.35)
Constant	-7.1949*	-7.0597*	-12.2577**	10.5613	9.7174
	(-1.92)	(-1.84)	(-2.26)	(1.01)	(0.85)
Daily fixed effects	N	N	Y	N	N
R-squared	0.0433	0.0528	0.2209	0.1095	0.1475
Observations	557	557	557	184	184
Test: Predicted Delay = Residual Delay					
F-statistics	10.9274***	7.2749***	14.8953***	0.5881	0.9625
p-value	0.001	0.0072	0.0001	0.4454	0.3295

Table 6. Overreaction to Stale News and the FTP-to-Public Delay

This table analyzes the relation between public investors' overreaction to news and the delay before filings possessed by the privately informed are released to the public. In both panels the dependent variable is the abnormal return, in percentage points, during (t_3, t_4), a period after immediate trading by the public on the news release and until the price reaches a steady state. Panel A analyzes the subsample with delays equal or shorter than 100 seconds, while the sample in Panel B is limited to filings that experienced a delay longer than 100 seconds. Both panels set t_4 to be d_5, the market close on the 5th day after the filing is released to the public. The first three columns of both panels set t_3 to be d_1, whereas the last three columns set t_3 to be $t_2 +$ 10 min. The coefficients of key interest are those of $AR(t_2, t_3)$. The t-statistics based on standard errors adjusted for heteroskedasticity are reported below the coefficients in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level.

Panel A: Filings with *Delay* $\leq$ 100 seconds

	(1)	(2)	(3)	(4)	(5)	(6)
		$t_3 = d_1$			$t_3 = t_2 +$ 10 min	
AR(t_2, t_3)	0.1615	0.1558	0.1625	0.3251	0.3267	0.3194
	(1.61)	(1.53)	(1.63)	(0.61)	(0.63)	(0.69)
Form 8K		-0.0028	-0.0020		0.0050**	0.0049
(News release)		(-0.76)	(-0.58)		(2.02)	(1.62)
Form 4		0.0028	0.0040*		-0.0066	-0.0076*
(Insider trading)		(1.33)	(1.70)		(-1.39)	(-1.78)
Schedule 13D		0.0170	0.0217		0.0197	0.0284**
(Activist block formation)		(1.22)	(1.59)		(1.48)	(1.98)
Constant	-0.0031***	-0.0038*	-0.0081*	-0.0034**	-0.0042**	-0.0091
	(-2.56)	(-1.67)	(-1.69)	(-2.57)	(-2.30)	(-1.35)
Daily fixed effects	N	N	Y	N	N	Y
R-squared	0.0135	0.0180	0.1354	0.0029	0.0115	0.1125
Observations	1,354	1,354	1,354	1,419	1,419	1,419

Panel B: Filings with *Delay* > 100 seconds

	(1)	(2)	(3)	(4)	(5)	(6)
		$t_3 = d_1$			$t_3 = t_2 + 10$ min	
AR(t_2, t_3)	-0.2240	-0.2325	-0.2161*	-0.3114*	-0.3241*	-0.2720**
	(-1.52)	(-1.60)	(-1.79)	(-1.83)	(-1.94)	(-1.99)
Form 8K		-0.0034	-0.0016		-0.0061	-0.0040
(News release)		(-0.81)	(-0.38)		(-1.27)	(-0.83)
Form 4		0.0050	0.0060*		0.0039	0.0063*
(Insider trading)		(1.63)	(1.88)		(1.30)	(1.86)
Schedule 13D		0.0721	0.0661		0.0711	0.0710
(Activist block formation)		(0.79)	(0.79)		(0.84)	(0.93)
Constant	-0.0056***	-0.0065***	0.0062	-0.0071***	-0.0071***	0.0132
	(-3.52)	(-3.17)	(0.91)	(-4.36)	(-3.56)	(1.29)
Daily fixed effects	N	N	Y	N	N	Y
R-squared	0.0286	0.0416	0.1680	0.0090	0.0220	0.1389
Observations	1,070	1,070	1,070	1,147	1,147	1,147