Information Processing Frictions and Price Informativeness: Evidence from a Natural Experiment

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Abstract

We isolate frictions at the acquisition and integration stages of information processing by leveraging a policy that led to users of the Securities and Exchange Commission's online repository of company reports failing to consult the disclosures they had requested. Exploiting this plausible source of exogenous variation in news access in a difference-in-differences design, we find that price informativeness is lower after a filing's submission if its potential viewers experience more failures and if they process more new reports by other firms. Our results provide empirical evidence for the three-step framework proposed in the literature to understand investors' use of information.

Keywords: Information frictions; Information acquisition; Information integration; Investor distraction; SEC EDGAR; EDGAR Log File Data Set; HTTPS-Only Standard

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1 Introduction

One of the most important functions of financial markets is price discovery, which entails the impounding of new information into security prices through trading. Blankespoor et al. (2019) and Blankespoor et al. (2020) argue that investors need to follow three steps (i.e., information awareness, information acquisition, and information integration) to process news about a company and spur price discovery. First, they must find out that recently disclosed information exists. Second, they must obtain the company disclosure or the press article reporting the news. Finally, they must analyze the new information and assess how it relates to firm value.

The theoretical literature has established the importance of each stage of information processing for price discovery by analyzing the impact of costs specific to the awareness stage (DellaVigna and Pollet, 2009; Hirshleifer and Teoh, 2003; Hirshleifer et al., 2011), acquisition stage (Fishman and Hagerty, 1989, 1992; Grossman and Stiglitz, 1980; Kyle, 1989), and integration stage (Verrecchia, 1982). However, such isolation of frictions particular to each step has been complicated in empirical studies. It has therefore been challenging to test not only the role each stage plays for price informativeness, but also the more fundamental claim that each stage is distinct from the other two. For example, in papers examining the effect of investor distraction on the incorporation of new information into stock prices, it is difficult to pinpoint whether the negative relationship is due to investors being unaware of the news, knowing about the new information but being unable to view it, or accessing the news but having trouble converting it to asset pricing signals (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009).

In this study, we empirically explore the impact on price informativeness of frictions that can be cleanly attributed to information acquisition and integration. We analyze the effects of preventing investors who *undoubtedly* have learned about the availability of new information from reading it and varying the capacity of investors who *for sure* have viewed the news to interpret it correctly. We show that these frictions have a negative impact on price informativeness, supporting previous theoretical findings and—perhaps more importantly—providing strong empirical evidence for the three-step framework proposed by Blankespoor et al. (2019) and Blankespoor et al. (2020) to understand investors' use of information.

The information events we examine are the publication of a company's disclosures at the online repository of the Securities and Exchange Commission (SEC), called the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. Regulatory filings have significant information content, as evidenced by large price movements that have been documented around their submission dates (Lerman and Livnat, 2010; Li and Ramesh, 2009; You and Zhang, 2009). We focus on these news events since we are able to know through a unique dataset the log details of all individual users who request access to download firm disclosures from EDGAR. Publicly available on the SEC website,[1] the EDGAR Log File Data Set allows us to study a group of investors who unquestionably know of the presence of a new company report and observe their information sets.

To identify the effect of frictions during the second step of information processing, we exploit as a natural experiment a rule enforced by the SEC website on June 20, 2016. This policy disallowed access to plain Hypertext Transfer Protocol (HTTP) web pages (e.g., http://sec.gov) and started redirecting HTTP requests toward encrypted Hypertext Transfer Protocol Secure (HTTPS) web pages (e.g., https://sec.gov), which are safer and less vulnerable to cyber attacks. We determine that after this unannounced change, some of these automatic redirections failed—possibly owing to a browser plugin or a firewall disabling redirects for security purposes—and some IP addresses were unable to access the filings they had requested to download.[2] This setup provides a plausible source of exogenous variation in news access among IP addresses who have passed the information awareness step.

We evaluate the impact of disruptions during information acquisition on three variables that are associated with price informativeness, namely, the percentage of cumulative abnormal return (CAR) around the disclosure date revealed on the filing date, report-date trading volume as a frac-

[1] See https://www.sec.gov/dera/data/edgar-log-file-data-set.html.

[2] Unsuccessful redirects persisted at least until June 30, 2017. While some IP addresses learned about the HTTPS policy and were subject to less unfulfilled redirections after the first trading day they experienced problems, a nonnegligible number of them continued to have failed redirected requests well over a year after June 20, 2016. This may be explained by some system administrators not permitting HTTPS traffic since HTTP was the prevalent protocol at that time and blocking the rarely used HTTPS port is a good security measure to prevent cyber attacks.

tion of total volume around the submission date, and filing-date abnormal idiosyncratic volatility (Dávila and Parlatore, 2018; DellaVigna and Pollet, 2009; Weller, 2018; Yang et al., 2020). We employ a difference-in-differences design to examine how the relationship between the outcome variables and the logged number of IP addresses *trying* to view a firm's newly-published filings is affected by the exposure of these IP addresses to unsuccessful redirections owing to the SEC website rule. To mitigate endogeneity concerns, exposure is defined as the average failure rate of IP addresses' requests for disclosures, made public before the company's report date, that they also try to consult. By excluding recently-filed SEC reports, we aim to capture IP address-level exposure to unfulfilled redirections that is orthogonal to both firm and filing characteristics.[3]

Our baseline results are consistent with frictions that can be directly assigned to the second stage of information processing impeding price informativeness. A greater number of IP addresses attempting to consult a company's recently-published disclosures is associated with a higher value for all three outcome variables. This positive effect is in turn weakened by the IP addresses' exposure to unsuccessful redirections. A one-standard deviation (SD) increase in exposure lessens the impact of a one-SD rise in the logged count of potential downloaders on the ratio between filing-day abnormal return and the CAR by 35%, the ratio between filing-day trading volume and the total long-term trading volume by 25%, and abnormal idiosyncratic volatility by 32%.

The validity of our difference-in-differences design rests on two main identifying assumptions. First, in the absence of exposure, there must be no systematic differences in the trends of price informativeness among firms with different exposures. Second, there must be no carryover effects of exposure on a specific day to other days. In line with the soundness of our empirical strategy, we show that there are no pre and post-trends among firms with different levels of exposure, where the trends are evaluated for either the reporting days or the calendar days surrounding the submission date. The results of two placebo tests further support the reasonability of the equal trends assump-

[3]Concerns may be raised if we instead use the failure rate of IP addresses' requests for a particular company's filings to calculate the same firm's exposure to unfulfilled redirects. For instance, suppose that an IP address' connection is lost after receiving a redirection. Upon the resumption of the connection, they may opt not to retry to access the filing if they become aware of a more important report published while they are offline. Here, the first filing being related to lower price informativeness is attributable to its lower information content.

tion.[4] Additionally, our baseline findings are not due to IP addresses with higher exposure being less sophisticated and they withstand a series of robustness checks.

The second part of the study seeks to disentangle the impact on price informativeness of frictions at the information integration step from those at the earlier two. To this end, we explore the effect when IP addresses who view a filing have less capacity to integrate new information. Given that the last stage of information processing consumes a considerable amount of investors' resources, we follow the investor distraction literature, and argue that reading other firms' newly-published reports reduces the time and effort IP addresses spend for the integration of a particular company's filings (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Kempf et al., 2017; Peress and Schmidt, 2020).

We deal with concerns that may arise if we just compare companies whose IP addresses read more disclosures by other firms with those whose IP addresses read less by once again leveraging the HTTPS policy in a difference-in-differences design.[5] We investigate the impact on the proxies for price informativeness of the triple interaction of the logged count of IP addresses trying to download any of a firm's new reports, the exposure variable, and a measure of potential distraction these IP addresses are subject to. Potential distraction is the logged average of the number of other-industry companies that are likewise attempted to be viewed by the IP addresses. Our findings indicate that what impairs price informativeness is not only IP addresses' intention to download other companies' disclosures, which may be owing to their anticipation of the quality of the information contained in a specific firm's filings, but also their actual reading of the other reports. The conclusions remain valid if, for the potential distraction measure, we only consider other-industry reports attempted to be consulted *before* IP addresses try to download a particular firm's disclosures. Successful reading of other companies' disclosures even before knowing the information content of a particular firm's reports also hinders price informativeness.

[4] One placebo test also establishes that the exposure measure is an IP address characteristic and not a firm characteristic, making its orthogonality to firm-level variables more plausible.

[5] For example, IP addresses may decide not to devote any effort to process a disclosure if it is either hard to interpret or inconsequential for stock prices. This frees up the investors' resources, allowing them to consult more filings from other firms. Price informativeness being lower when IP addresses view other companies' filings may be a symptom of SEC reports' low readability or little relevance for firm value.

Our paper contributes to the literature in three ways. The first contribution is the identification of frictions specific to the acquisition and integration stages of information processing and the determnination of their impact on price informativeness. In doing so, we provide robust empirical evidence for the three-step framework advanced by Blankespoor et al. (2019) and Blankespoor et al. (2020) to facilitate the understanding of how investors use information for their trading decisions. A study that also strives to disentangle frictions at the different stages of information processing is that of Blankespoor et al. (2019), who investigate the effect on abnormal volume if the Associated Press' automated articles of companies' earnings announcements also include the analyst consensus. They compare firms whose articles are with and without the analyst consensus, and argue that the former are subject to lower information acquisition costs. We believe that our empirical strategy allows for a cleaner isolation of information processing frictions since we are able to observe *individual* IP addresses' intended and actual information sets. We are thus certain that the IP addresses we examine are aware of a company's new SEC filings.

Our second contribution is presenting strong, more recent evidence for the important role the SEC's electronic repository plays for the assimilation of new information into asset prices. Gao and Huang (2020) and Goldstein et al. (2020) use the staggered rollout of EDGAR in the 1990s to show that it increased the total amount of information in prices. While other earlier studies have put into question the importance of EDGAR for price informativeness (Chang and Suk, 1998; Lawrence et al., 2018; Li et al., 2011; Schaub, 2018), we are able to control for the effect of alternative news sources and cleanly isolate the impact on price informativeness of news gathering via EDGAR through our strategy exploiting a novel source of plausibly exogenous variation in information acquisition. To the best of our knowledge, we are the first to employ the HTTPS policy of the SEC website in an empirical analysis. Our methodology is related to that of Heilig et al. (2021), who consider a different natural experiment that led to many unfulfilled requests (i.e., an unexpected outage of the EDGAR server on April 24, 2017) and demonstrate its effect on stock liquidity.

Lastly, our study is related to prior research that analyzes the effect of investor distraction on market outcomes. Establishing that the reading of other disclosures affects the processing of a downloaded filing allows us to identify the impact of distraction during the information integration step of information processing. In most studies in the literature, investor distraction cannot be directly attributed to the awareness, acquisition, or integration stages (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Kempf et al., 2017; Peress and Schmidt, 2020). If we can assume that an analyst at least reaches the acquisition stage when processing the earnings announcements of all the firms they follow, then a notable exception is the work by Driskill et al. (2020). They find that the analyst's issuance of a company's earnings forecasts is less timely when it announces its earnings on the same day as other companies covered by the analyst. Our results complement this paper by demonstrating that EDGAR users can also suffer distraction after the acquisition step and showing that investors being distracted while integrating information has adverse effects on price informativeness.

The remainder of the paper proceeds as follows. Section 2 describes the natural experiment that constitutes the backbone of our empirical analysis. The data and the construction of the sample are explained in Section 3, while the difference-in-differences design is detailed in Section 4. The findings related to frictions during information acquisition and integration are in Sections 5 and 6, respectively. Section 7 concludes.

2 The SEC's HTTPS Policy

On June 8, 2015, the White House Office of Management and Budget released memorandum M-15-13, entitled "Policy to Require Secure Connections across Federal Websites and Web Services."[6] This memorandum required that all websites of the Federal government be accessible only through an HTTPS connection by December 31, 2016. The objective was to protect the privacy and enhance the security of the general public while interacting with US government websites. At that time, the dominant protocol for web communication was HTTP. Client requests and server responses sent using HTTP can however be easily intercepted and altered, making users suscep-

[6]See https://www.whitehouse.gov/sites/whitehouse.gov/files/omb/memoranda/2015/m-15-13.pdf. A web-friendly version is available at https://https.cio.gov.

tible to eavesdropping, tracking, and man-in-the-middle attacks. An HTTPS connection is less vulnerable to these threats since it encrypts almost all of the exchanged information.

In adherence to the HTTPS-Only Standard, the SEC website started automatically diverting requests for HTTP webpages to their HTTPS versions in between June 20, 2016, and June 22, 2016.[7] Whenever a client is redirected from HTTP to HTTPS, the server responds with an HTTP Status Code 301 ("Moved Permanently"). This informs the client that the requested resource from then on can only be viewed at a new address. For all trading days from January 2, 2015, to June 30, 2017, we employ EDGAR's dataset of user logs and calculate the percentage of all attempts to download newly-filed SEC reports that return a 301 code. An attempt is defined as a pair of an IP address and an SEC filing, and it is considered to be redirected if a code 301 is received at least once before the end of the trading day. From Figure 1a, one observes that the fraction of redirected attempts is close to zero before June 20, 2016. The percentage of attempts with a 301 response noticeably jumps to 16% on June 20, 2016, and does not go below 4% until June 30, 2017. In between these dates, the average percentage of redirected attempts is 17%. These findings point to June 20, 2016, as the first trading day during which automatic redirections were implemented.

Usually, clients' web browsers follow a redirect and automatically send another request for the HTTPS web page. However, this is not always the case.[8] One possible reason is that a browser plugin or a software (e.g., a firewall) may be disabling redirects for security purposes.[9] Other potential explanations for diverted clients not reaching the HTTPS webpage are mentioned in Section OA.3 of the Online Appendix. Indeed, we observe that some of the redirected attempts by IP addresses to consult newly-available filings did not materialize into successful downloads. Figure 1b shows the daily percentage of redirected attempts that ultimately fail on and after June 20, 2016.

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[7] The steps Federal websites needed to follow to adhere to the memorandum is explained in Section OA.1 of the Online Appendix (See https://www.shorturl.at/mrGV9). We discuss in Section OA.2 of the Online Appendix how we determine when the SEC began redirecting HTTP traffic to HTTPS.

[8] According to the guidelines promulgated by the Internet Engineering Task Force (i.e., the organization that develops Internet standards), the client receiving a code 301 "[may] use the [new address sent by the server] for automatic redirection" (Fielding and Reschke, 2014). In other words, clients are not obligated to follow the redirect to the new web page.

[9] If all automatic redirections were allowed, a user could click on a seemingly harmless link sent by an attacker and be redirected to a malicious website.

An attempt is considered successful if an HTTP Status Code between 200 and 226 ("Successful") is registered before the end of the trading day. The failure rate of redirected attempts starts at 41% on June 20, 2016, reaches its maximum of 69% on March 1, 2017, and ends at 22% on June 30, 2017. During this period, the mean daily percentage of failed redirected attempts is 24%.

The SEC's implementation of the HTTPS-Only directive led to a general increase in the failure rate of attempts to view *any* report (i.e., not just the recently published disclosures). Throughout the whole sample period, we plot in Figure 1c the daily percentage of all IP-filing pairs that do not receive a successful HTTP Status Code any time before the trading day ends. Before the SEC's HTTPS policy, almost all attempts are fulfilled. The fraction of failed attempts undergoes a notable level change on June 20, 2016. We categorize the unsuccessful attempts into those that are accompanied by a code 301 and those that are not.[10] In Figure 1d, we obtain that a very negligible part of the unfulfilled attempts are due to redirects before June 20, 2016. In contrast, virtually all of the unsuccessful attempts on the EDGAR server are characterized by a redirection after the start of the SEC website's policy. After June 20, 2016, the daily percentage of attempts that are both redirected and unfulfilled achieves a maximum of 30% with a mean of 10%.

A question one could ask is why the failed download attempts owing to disrupted redirects persisted months after June 20, 2016. If users are unable to access SEC reports, they could investigate the issue, realize that it is because of the SEC website's redirections to HTTPS, and request access directly to the secure address. We document that some IP addresses indeed learned about the policy and were subject to less unfulfilled redirects after experiencing them. We consider IP addresses whose attempts to view any filing are all redirected and unfulfilled on the first day after June 20, 2016, they are active on EDGAR. Figure 1e plots the average across these IP addresses of the fraction of attempts that are both redirected and unsuccessful in the next activity days following the first. The average proportion plummets to 53% in the second activity day and remains at around 40% in the next 148 visits. That the mean percentage does not drop to zero suggests that

[10] Other codes that are returned include HTTP Status Code 400 ("Bad request"), 403 ("Forbidden"), 429 ("Too many requests"), 500 ("Internal server error"), 502 ("Bad gateway"), 503 ("Service unavailable"), and 504 ("Gateway timeout").

some IP addresses might have been barred from accessing HTTPS websites (e.g., due to security reasons). Aside from this, there were unsuccessful redirects more than a year after the start of the policy since there were always first-time visitors—who possibly had not learned about the new rule yet—every day after June 20, 2016. As seen in Figure 1f, at least 44% of all IP addresses active each week record their first post-policy log.

3 Data

We isolate the effect on price informativeness of frictions at the two latter stages of information processing by exploiting this natural experiment in a difference-in-differences design. The pre-policy period consists of the 180 trading days before the start of the HTTPS policy (i.e., from October 1, 2015, to June 19, 2016), while the post-policy period consists of the 180 trading days after (i.e., from June 20, 2016, to March 8, 2017).[11] We combine various data sources to construct an unbalanced firm-level panel dataset of the price informativeness of stock prices whenever companies submit an SEC report through EDGAR.

3.1 Sample construction and data sources

We obtain a list of all reports electronically filed through EDGAR from October 1, 2015, to March 8, 2017, from the SEC website. We then determine the exact date and time at which the filings are accepted by reading the timestamps in the header of each submission file. Documents accepted after trading hours are assigned the next trading day as their submission date. We restrict the analysis to disclosures that the market deems relevant for setting a firm's stock price. We proxy the information content of all of company i's filings on trading date t by the long-term price reaction around t. In particular, the amount of information revealed through the SEC reports is measured by the cumulative abnormal return $CAR^{-10,20}$ from $t-10$ to $t+20$, where abnormal return is the CAPM alpha and the CAPM beta is estimated using the period from $t-70$ to $t-11$. Firm-days

[11] We consider different windows around June 20, 2016, in Section 5.5.

with $CAR^{-10,20}$ in between -5% and 5% are not considered.[12] Table OA.1 of the Online Appendix reports the frequency of filing types in the final sample.

We employ the EDGAR Log File Data Set to get our main explanatory variables. This database, which covers the period from February 2003 to September 2017, includes information on, among others, the partially anonymized IP address of each user logging on to EDGAR, the date and time of the visit, the document consulted, and the HTTP Status Code. We exclude EDGAR logs that are not to the documents themselves but to an index of a set of filings. We further remove logs that are potentially by non-humans (e.g., bots). We detect these instances by (i) employing the web traffic database' indicator variable for users that self-identify as web crawlers and (ii) determining for each day the activity of IP addresses that successfully view more than 50 unique filings or attempt to download more than 100 (Lee et al., 2015). Similar to the date adjustment made for company filings, logs that occur after hours are assigned the next trading day as the page visit date.

We use the following data sources to construct the other variables. Daily closing prices, returns, volume, and shares outstanding are from the Center for Research in Security Prices (CRSP) database. In line with previous studies, we focus on common shares; stocks traded on NYSE, AMEX, or NASDAQ; and stocks whose price is greater than 1 USD. Minute-by-minute closing prices for 441 of the most actively traded stocks are from Pi Trading. Institutional investor ownership is from the Thomson Reuters Institutional Holdings (13F) database. The Institutional Brokers' Estimate System (I/B/E/S) provides information on the analysts following a stock and the earnings announcement dates of a number of firms. Data on the book value of common equity and the earnings announcement dates of the remaining firms are from Compustat. Whenever Compustat and I/B/E/S disagree on the earnings announcement date, we follow DellaVigna and Pollet (2009) and keep the earlier of the two dates.

[12] In Section 5.5, we show that our results continue to hold for other evaluation period lengths and factor models used to compute abnormal returns, and other threshold values for cumulative abnormal returns used to exclude observations.

3.2 Variable definitions

Our main independent variables are *Log(IPs1)*, measuring intended news-reading activity, and *ErrorExp*, measuring the exposure to unsuccessful HTTPS redirections of IP addresses attempting to download a firm's filings. The first is the logged number of IP addresses who satisfy two conditions. To be counted for firm i's value of *Log(IPs1)* on report date t, IP addresses must attempt to consult (i) at least one of i's disclosures submitted on t and (ii) at least one filing published before t. We discuss the justification for imposing the second restriction below. Let $\mathcal{J}_{i,t}$ be the set of such IP addresses and $\mathcal{F}_{j,t}$ the set of disclosures published before t that an IP address j tries to view on t. The second explanatory variable is the average of the failure rates $\omega_{j,t}$ across all js in $\mathcal{J}_{i,t}$, where

$$\omega_{j,t} = \frac{1}{|\mathcal{F}_{j,t}|} \sum_{f \in \mathcal{F}_{j,t}} \mathbb{1}_{Fail}(j,f,t) = \frac{1}{|\mathcal{F}_{j,t}|} \sum_{f \in \mathcal{F}_{j,t}} \mathbb{1}_{HTTPS}(t) \mathbb{1}_{301}(j,f,t) \left[1 - \mathbb{1}_{200}(j,f,t)\right]; \qquad (1)$$

$\mathbb{1}_{Fail}(j,f,t)$ is an indicator variable that equals one if j's attempt to download f fails on t and zero otherwise; $\mathbb{1}_{c}(j,f,t)$ is an indicator variable that equals one if the attempt returns an HTTP Status Code of $c \in \{200, 301\}$ at least once on t and zero otherwise; and $\mathbb{1}_{HTTPS}(t)$ is an indicator variable that equals one if t falls on or after June 20, 2016, and zero otherwise. IP address j's attempt to consult f on t is counted as a failure due to the HTTPS policy if it (i) occurs after June 20, 2016, (ii) is redirected at least once during t, and (iii) is never successful throughout t.

One may contend that a more natural way of obtaining firm i's exposure on report date t is (i) first calculating the failure rate in Equation (1) as the mean of $\mathbb{1}_{Fail}(j,f,t)$ over i's newly-published filings that j intends to consult on t and then (ii) averaging the failure rates across IP addresses who attempt to read any of i's disclosures on t. This however is subject to endogeneity concerns. For instance, suppose that an IP address' connection is lost after receiving a code 301. Upon the resumption of the connection, they may opt not to retry to access the filing if they become aware of a more important report published while they are not connected to the Internet. In this case, obtaining that the first filing is related to lower price informativeness than the second is owing to its lower information content and not to the IP address' inability to read the contents of the first.

Since we calculate IP address j's failure rate over filings published before t, it is more likely that $\omega_{j,t}$ captures the exposure of j to the HTTPS policy and not their strategic choices brought about by actual or perceived differences in the information content of newly-published filings. Our definition of the failure rate requires that IP addresses attempt to consult at least one filing submitted before t, explaining the second requirement for inclusion in $\mathcal{J}_{i,t}$. Firm-days without such IP addresses are dropped from the sample. We control for the excluded IP addresses (i.e., those who request for i's disclosures filed on t but are not in $\mathcal{J}_{i,t}$) by accounting for *Log(OthIPs1)*, defined as the logged number of all potential downloaders of i's reports minus *Log(IPs1)*.

We use three proxies for the informativeness of filing-day prices. The first, *PctAR*, is the proportion of the total information contained in the disclosures revealed through prices on the report date t. It is defined as the ratio between date-t abnormal return and the cumulative abnormal return (CAR) from $t-10$ to $t+20$ (DellaVigna and Pollet, 2009; Weller, 2018).[13] The second proxy is *PctVolume*, which is the ratio between date-t trading volume and the cumulative trading volume from $t-10$ to $t+20$. Dávila and Parlatore (2018) find that trading volume is positively correlated with the information content of prices, a relation that can be explained by investors trading more if they have more precise information.

Following Yang et al. (2020), our third proxy for price informativeness is abnormal idiosyncratic volatility. Idiosyncratic volatility of firm i on filing date t is the standard deviation of the residuals from the intraday regression of i's 5-minute returns on the 5-minute returns of the market. Market return is the value-weighted returns of stocks included in the Pi Trading database. When informed investors trade more and impound more information into prices, the part of stock returns unexplained by the market model becomes more volatile. To control for the confounding effect of business and financial risk on idiosyncratic volatility, we subtract the average idiosyncratic volatility from $t-11$ to $t-30$ from the idiosyncratic volatility on t in calculating our third proxy, *AbIdVol*.

The construction of the control variables is detailed in Section OA.4 of the Online Appendix.

[13] This variable is very noisy for small values of the long-term price response. This is another reason for dropping observations for which the absolute value of $CAR^{-10,20}$ is less than 5%.

A summary of all the variables we use in the study, together with their respective definitions, is in Panel A of Table 1. All variables, except for those derived from the EDGAR Log File Data Set, are winsorized at the 1% and 99% levels.

3.3 Summary statistics

The dataset is an unbalanced firm-level panel with 68,349 observations made up of 3,110 unique firms, 361 trading days from October 1, 2015, to March 8, 2017, and 149,851 filings. The average firm appears 22 times in the dataset, which implies that it has at least one disclosure every 16 days. Summary statistics are presented in Panel B of Table 1. On average, 16 users attempt to view at least one newly-published SEC filing on the first trading day it becomes public. Out of them, 12 likewise try to consult a report published previously. Some filings receive only one download attempt, while the maximum number of potential viewers is 8,085. After June 20, 2016, the average exposure of reporting firms to unsuccessful redirections is 6.8%. Around 60% of observations have zero exposure to the HTTPS policy. The mean value of the filing-date abnormal return as a percentage of $CAR^{-10,20}$ is 6.8%, while report-date trading volume is 4.1% of the 31-day cumulative volume around submission. Average abnormal idiosyncratic volatility is 0.05%.

By excluding newly-filed SEC reports in calculating the average failure rate of IP addresses, our definition of *ErrorExp* aims to capture IP address-level exposure to unfulfilled redirections that is orthogonal to both firm and filing characteristics (e.g., the amount and type of information contained in the disclosure). Table OA.2 of the Online Appendix reports the correlations of exposure to failed redirections with other variables. The absolute values of the correlations are generally low; the majority are below 0.1. Notable exceptions are the dummies for current reports (correlation of -0.14) and for filings that disclose the trading of company insiders (correlation of 0.16).[14]

[14] We examine this issue in Section 5.5 and show that controlling for the filing type does not alter our baseline results.

4 Empirical strategy

We start by first estimating the effect of frictions at the information acquisition stage on price informativeness. We implement a difference-in-differences design exploiting time-varying firm-level variation in *ErrorExp* by running the following two-way fixed-effect panel regression

$$Y_{it} = \alpha Log(IPs1)_{it} \times ErrorExp_{it} + \mu Log(IPs1)_{it} \times + \mathbf{X}_{it}'\gamma + \psi_i + \xi_t + \varepsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is a proxy for firm i's price informativeness on filing date t, $\mathbf{X}_{it}$ is a vector of controls, ψ_i is the firm fixed effect, ξ_t is the filing day fixed effect, and the other uninteracted term is omitted for conciseness. The main variable of interest is the interaction between intended news reading activity and the firm's exposure to unsuccessful redirections due to the SEC's HTTPS policy. A positive value for μ and a negative value for α is consistent with disruptions during information acquisition impairing price informativeness since they imply that frictions at the second stage of information processing moderate the positive impact of *Log(IPs1)* on the outcome variables.

Aside from the control variables discussed in Section OA.4 of the Online Appendix, $\mathbf{X}_{it}$ likewise includes fixed effects for the time the earliest report is electronically submitted on the filing date. The literature finds heterogeneity in investor attention throughout the day (deHaan et al., 2015; Kraft et al., 2020; Michaely et al., 2014; Patell and Wolfson, 1982). To take the confounding effect of time-varying investor attention into account, we control for dummy variables for each 30-minute interval company filings are accepted by the SEC.[15] Another advantage of saturating the regressions with filing time fixed effects is that we can rule out that our findings are owing to managers strategically choosing when to make disclosures public during the day.[16]

The main identifying assumptions for Equation (2) are that (i) there are no systematic differ-

[15] We document in Figure OA.1 of the Online Appendix that our three measures of price informativeness systematically vary throughout the trading day. Interestingly, price informativeness is highest if the firm submits its first disclosure in the morning before markets open.

[16] For example, bad news are more likely to be made public when markets are closed (deHaan et al., 2015; Michaely et al., 2016; Segal and Segal, 2016). Moreover, Doyle and Magilke (2009), and Michaely et al. (2014) contend that attention is high after regular trading hours, driving managers to release more complex news during this period to facilitate information dissemination.

ences in the trends of price informativeness across firm-days with different *ErrorExp* in the absence of the exposure and (ii) there are no carryover effects to other days of the exposure to failed redirects. Notice that we cannot employ the usual approach to assess the parallel trends assumption for a difference-in-differences estimation with a time-invariant treatment, wherein the common trend is only checked pre-policy. Our exposure variable is not necessarily constant after June 20, 2016. Some firms post-policy can have positive exposure on one day and zero exposure the next. That is, a firm can both be treated and untreated after the SEC's HTTPS policy. For this same reason, the second assumption on the absence of carryover effects must additionally be imposed. If it does not hold, finding a statistically significant effect of the main interaction on price informativeness could be owing to a firm's past exposure to unfulfilled redirections and not to the current one. We test both assumptions by verifying whether the values of the interaction between *ErrorExp* and *Log(IPs1)* in the previous and next days have an impact on current price informativeness.

5 Information acquisition frictions and price informativeness

5.1 Baseline results

Table 2 presents the estimated impact of exposure to unfulfilled redirects on the percentage of CAR revealed on the filing date, the percentage of cumulative volume attributable to the filing date, and abnormal idiosyncratic volatility. All regressors are standardized except for *ErrorExp*, which is not demeaned but set to have unit standard deviation (SD) after the HTTPS policy. Standard errors are two-way clustered at the firm and the filing date levels. The results in the odd-numbered columns report the coefficient estimates when the exposure variable is first suppressed from the regressions. Similar to Drake et al.'s (2015) results based on *successful* views of SEC reports, we find that the number of IP addresses attempting to download a filing is positively related to our three proxies for price informativeness. In particular, a one-SD increase in *Log(IPs1)* is associated with an increase in *PctAR* by 1.6 pp, *PctVol* by 0.6 pp, and *AbIdVol* by 0.02 pp.

We reintroduce the measure of a firm-day's exposure to unsuccessful redirections in the even-numbered columns. In line with our prediction, we obtain that the positive effect of *Log(IPs1)* on price informativeness is moderated by *ErrorExp*. Going from an exposure of 0% to 14.6% (i.e., a one-SD change) lowers the impact of a one-SD increase in *Log(IPs1)* on the ratio between filing-day AR and the long-term price response by 35%, the ratio between filing-day trading volume and the cumulative long-term trading volume by 25%, and abnormal idiosyncratic volatility by 32%.

5.2 Testing the identifying assumptions: Pre and post-trends

The validity of the difference-in-differences design can be assessed by demonstrating that there are no trends in the effect of the current value of the interaction between *ErrorExp* and *Log(IPs1)* on the leads and lags of price informativeness. We test the two identifying assumptions by running the regression

$$Y_{i,t} = \sum_{t'=-10}^{10} \eta_{t'} \mathit{Log(IPs1)}_{i,\tau(i,t,t')} \times \mathit{ErrorExp}_{i,\tau(i,t,t')} + \psi_i + \xi_t + \varepsilon_{i,t}. \tag{3}$$

Let $T_i = (t_{i,1}, t_{i,2}, ..., t_{i,N_i})$ be the ordered set of dates in the sample period on which firm i submits at least one SEC report. The function $\tau(i,t,t')$ signifies the date in T_i that is t' positions before t. That is, $Z_{i,\tau(i,t,t')}$ is a variable Z's lag-t' value if t' is positive or its lead-$|t'|$ value if t' is negative. The leads and lags of the uninteracted terms are omitted in Equation 3 for brevity. For t' less than zero, the coefficient $\eta_{t'}$ corresponds to the effect of the current value of the main interaction term on the outcome on the filing date that is t' positions before t. Conversely, it represents the impact of the current value of the interaction between *Log(IPs1)* and *ErrorExp* on price informativeness t' positions after t when t' is greater than zero.

Non-violation of the assumption on trends can be checked by verifying that $\eta_{t'}$ is equal to a constant $\hat{\eta}$ for negative t'. Similarly, the main interaction term not having any carryover effects means that for any positive t', $\eta_{t'}$ is equal to $\hat{\eta}$. The estimates of $\eta_{t'}$, together with the 95% confidence intervals, for t' spanning from -10 to 10 are displayed in Figure 2. For all proxies of price informativeness, there are no significant differences in the impact of the current value of the interaction between *Log(IPs1)* and *ErrorExp* on lagged outcomes. The effect of the interaction term seems to only be present on the filing date itself, as $\eta_{t'}$ for positive t' reverts immediately to its level before $t' = 0$. Taken together, these findings provide strong evidence for the soundness of our empirical strategy.

These results corroborate the identifying assumptions in *event time*. We likewise assess these assumptions in *calendar time* by running an event study, and exploring whether the main interaction term has an impact on price informativeness on the trading days right before and after the report date. For each firm and filing date pair, we calculate the proxies for price informativeness from 10 days before to 20 days after the report date. We then run the following regression at the firm-filing-date-trading-date level:

$$\begin{aligned} Y^s_{i,t} =& \theta_{-10} \mathit{Log(IPs1)}_{i,t} \times \mathit{ErrorExp}_{i,t} + \sum_{s'=-9}^{20} \left(\theta_{s'} - \theta_{-10}\right) \mathbb{1}_{s'}(s) \times \mathit{Log(IPs1)}_{i,t} \times \mathit{ErrorExp}_{i,t} \\ &+ \psi_i + \xi_{t+s} + \varepsilon^s_{i,t}, \end{aligned} \tag{4}$$

where $Y^s_{i,t}$ is the outcome variable for firm i s days from filing date t, $\mathbb{1}_{s'}(s)$ is an indicator variable that equals one if s is equal to s' and zero otherwise, ψ_i is the firm fixed effect, ξ_{t+s} is the trading day fixed effect, and the uninteracted terms are omitted for brevity. For s' from -10 to 20, the coefficient $\theta_{s'}$ represents the impact of the interaction between filing-date *Log(IPs1)* and *ErrorExp* on price informativeness s' days from the submission date.

As in the event-time analysis, obtaining that $\theta_{s'}$ is equal to a constant $\hat{\theta}$ for negative s' is consistent with the validity of the equal trends assumption. If $\theta_{s'}$ returns to $\hat{\theta}$ for positive s', then it once again confirms the absence of carryover effects. The estimates of the coefficient of the main interaction term, together with their 95% confidence intervals, are graphically reported in Figure 3. For the three measures of price informativeness, the estimates for $\theta_{s'}$ for negative s' are not significantly different from each other. Apart from justifying the parallel trends assumption, this also rules out that the exposure to unsuccessful redirects is anticipated and bolsters the case for the exogeneity of *ErrorExp*.

The effect of the main interaction term is significantly negative and undoubtedly the most pronounced on the filing date (i.e., when s' is equal to zero). The estimate for $\theta_{s'}$ then goes back to its level before the submission date starting at s' equal to 1, except when the proxy is *PctVolume*. In this case, it does so beginning at s' equal to 2. We thus uncover some carryover effects when price informativeness is measured as daily volume as a percentage of 31-day cumulative volume, but they are rather short-lived. Given that the average length of time between successive report dates is 16 days, we do not expect the impact of the interaction between *Log(IPs1)* and *ErrorExp* on price informativeness a few days after the filing date to spill over to the next submission date. The lack of carryover effects in the event-time regressions supports this assertion.[17]

5.3 Testing the identifying assumptions: Placebo tests

Another way of testing the equal trends assumption is through a placebo test. Recall that *Error-Exp* is the average failure rate of IP addresses who are counted in the definition of *Log(IPs1)*. As discussed in Section 3.2, to mitigate endogeneity concerns, not all IP addresses who attempt to download any of a firm's newly-published reports are considered for *Log(IPs1)*. Our first placebo test entails treating these dropped IP addresses with the included IP addresses' exposure to unsuccessful redirections. We add to the regression specification in Equation (2) the interaction between *ErrorExp* with *Log(IPs0 − IPs1)*, which is the logged count of the excluded IP addresses. Since *ErrorExp* is not these IP addresses' exposure to failed redirections, fulfilling the parallel trends assumption involves having a zero impact of the new interaction term on price informativeness. If we instead find that the effect is statistically significant, it may mean that the exposure measure is not specific to the IP addresses attempting to consult a company's filings but the firm itself. The baseline impact we document may come from some underlying difference in trends among firms with different values of *ErrorExp*.

The results are reported in Table 3.[18] The odd-numbered columns contain the estimates when

[17]Furthermore, we show in Table OA.3 of the Online Appendix that the baseline findings continue to hold even when we drop consecutive firm-days from the sample.

[18]There are less observations as compared to Table 2 since firm-days that do not exclude IP addresses from the definition of *Log(IPs1)* are dropped from the sample.

the exposure measure is first suppressed from the regression model. A higher number of IP addresses attempting to download a filing, regardless of whether they are in the included or the excluded group, is strongly positively related to all outcome variables. Interacting *Log(IPs1)* and *Log(IPs0 − IPs1)* with *ErrorExp* in the even-numbered columns, we find that the exposure variable moderates the effect on price informativeness of a higher number of IP addresses, but only for the group whose average failure rate is precisely *ErrorExp*. These results are consistent with the equal trends assumption. Moreover, they establish that the exposure measure is a characteristic of IP addresses and not of a specific company, making its orthogonalilty to firm-level variables—including the quality of information contained in the new disclosures—more plausible.

The second placebo test we perform is related to regressing on the interaction between *Log(IPs1)* and *ErrorExp* outcome variables that should not be related to it. It has been documented that investors react to analysts' revisions of their forecasts of future firm performance (Gleason and Lee, 2003). If we obtain that the magnitude of analyst revisions during the report dates is associated with the main interaction term, then the effects on price informativeness we observe may be owing to investors's response to changes in analyst estimates and not to the exposure to unfulfilled redirects. That is, even absent the exposure, firms with different levels of *ErrorExp* would still differ in terms of price informativeness because they are subject to different degrees of analyst revisions.

We rerun Equation (2) while having as the dependent variables four measures indicating the extent to which analysts modify their forecasts of future EPS due to the submission of SEC reports. The first one, *RMSDOwnPre*, is the square root of the average squared deviation of analysts' own forecast at the end of t from their own estimate right before the publication of the first filing on t. The other three measures are differences between the root mean square deviation (RMSD) at the end of t and the RMSD immediately prior to the acceptance by EDGAR of the earliest disclosure on t. The deviations are those of an analyst's own estimate from either the median estimate right before the publication of the first report on t (*RMSDMedPreCh*), the analyst's own estimate at the end of $t+20$ (*RMSDOwnFutCh*), or the median estimate at the end of $t+20$ (*RMSDMedFutCh*). The construction of these variables are detailed in Section OA.5 of the Online Appendix.

If the coefficient of the main interaction term is negative and statistically significant when the outcome variable is either *RMSDOwnPre* or *RMSDMedPreCh*, then firm-days with a higher value of the interaction are also more likely to have analysts who do not revise their estimate of future EPS, violating the assumption on equal trends. Similarly, if the coefficient of interest is significantly positive when the dependent variable is the RMSD of an analyst's post-report estimate from forecasts after 20 days, then the baseline effects may come from price informativeness being lower when the interaction term is higher because analysts are slower at reacting to news. The regression results are reported in Table 4. In line with our difference-in-differences design fulfilling the parallel trends assumption, the estimates for the coefficient of the interaction between *Log(IPs1)* and *ErrorExp* are all statistically insignificant with a very low t-statistic.

5.4 Investor sophistication as alternative explanation

The first placebo test lends empirical support for our claim that our exposure measure is specific to the IP addresses trying to consult a filing, and is unlikely driven by firm and filing characteristics. One may however still argue that *ErrorExp* is proxying for the sophistication of the IP addresses. If users have already been browsing the Internet securely since they know about the SEC website policy or are technologically up-to-date, there is no need to be redirected as they can just go straight to the HTTPS web page of the filing. Furthermore, IP addresses with a 100% success rate in the latter part of the sample period may be the ones who are able to learn from the download problems they have had post-policy. Technical know-how may be positively correlated with financial expertise and price informativeness being lower when the exposure is higher may be owing to a filing having a less sophisticated investor base.

We pursue to rule out that investor sophistication is the sole driver of our findings. Suppose that the alternative mechanism is the only reason for our baseline results. This implies that an IP address' exposure to failed redirects can proxy for their level of unsophistication. We can then obtain a time-invariant proxy for the unsophistication of a particular IP address by computing their *total* failure rate—the percentage of all attempts from June 20,2016, to March 8, 2017, to download previously-published disclosures that are both redirected and unsuccessful. The mean of this variable is then calculated over all IP addresses with a non-missing total failure rate to get *TotErrorExp*, which is our firm-day-level measure of the average unsophistication of IP addresses trying to consult a firm's filing on the report date. Note that *TotErrorExp* can be non-zero before June 20, 2016, owing to IP addresses who attempt to consult a disclosure pre-policy experiencing unfulfilled redirections post-policy.

To test the primary importance of the alternative explanation, we replace *Log(IPs1)* in Equation (2) with *Log(IPs2)*, which is the logged number of IP addresses who try to consult at least one previously-published report (i) on the filing date and (ii) after June 19, 2016 (i.e., those with non-missing *ErrorExp* and *TotErrorExp*). We then incorporate the interaction between *Log(IPs2)* with *TotErrorExp* in the regression specification. If investor sophistication is the key factor underpinning our findings, then introducing the new interaction term should lead to the coefficient of the interaction between *Log(IPs2)* and *ErrorExp* to lose its statistical significance. The odd-numbered columns in Table 5 show that our baseline findings in Table 2 continue to hold even when considering a different subset of IP addresses. We interact *Log(IPs2)* with *TotErrorExp* in the even-numbered columns. We obtain that even after controlling for our proxy for investor unsophistication, the coefficient of the main interaction term is consistently negative and statistically significant, contradicting the principal role the alternative story plays for our baseline findings.

5.5 Robustness tests

Table OA.4 of the Online Appendix documents that our findings related to the effect of the main interaction term on the percentage of CAR revealed on the filing date are robust to (i) risk-adjusting returns using the Fama and French (1993) 3-factor model, the Fama and French (2015) 5-factor (FF5) model, or the FF5 model with Carhart's (1997) momentum factor; (ii) computing CAR until 5, 10, or 15 days after the report date; and (iii) dropping observations with CAR less than or equal to 1%, 2%, or 10% from the sample. As discussed in Section 3.3, the exposure variable is most correlated with two filing type dummies. We take these correlations into account by adding the interaction of five filing type dummies with *Log(IPs1)* to Equation (2). The results are in the odd-numbered columns of Table OA.5 of the Online Appendix. The coefficients of the interaction between *Log(IPs1)* and *ErrorExp* are still statistically significant, but their magnitudes are lower. The impact of the main interaction term become stronger under the even-numbered columns, where we additionally interact all the fixed effects with the logged count of IP addresses attempting to download a report. This step controls for the average sensitivity of the outcome variable to *Log(IPs1)* for each firm, trading day, and filing time. Lastly, we show in Table OA.6 of the Online Appendix that the negative and statistically significant effect of the interaction between *Log(IPs1)* and *ErrorExp* remains if we consider other sample periods, namely, 60 days, 120 days, or 240 days before and after June 20, 2016.

6 Information integration frictions and price informativeness

The previous section empirically isolates the effect of frictions at the information acquisition stage by documenting that a plausibly exogenous negative shock to IP addresses' ability to view a filing they intend to download leads to less informative prices. In the same vein, the goal of the remainder of the study is to decouple the impact on price informativeness of frictions at the third step from those at the two earlier ones. Information integration uses up a considerable amount of investors' resources as it entails extracting signals from a filing, understanding them, and converting them into inputs to an asset pricing model.

Following the investor distraction literature, our approach is to examine whether the news reading of other SEC reports has a distracting effect on the IP addresses who are processing a specific firm's reports (DellaVigna and Pollet, 2009; Hirshleifer et al., 2009; Kempf et al., 2017; Peress and Schmidt, 2020). Since human cognitive capacity is limited, the time and effort IP addresses spend for the integration of information contained in a disclosure may be reduced if they also dedicate a portion of their resources to interpret other unrelated filings. In this case, the signals they acquire about the report of interest could be less precise or they could be more likely to commit mistakes while determining the consequences of the news for the firm's stock price. We expect price informativeness to be lower when IP addresses consulting a company's newly-published filings also download more newly-submitted disclosures from other companies.

One may attempt to test this claim by regressing the proxy for price informativeness on the interaction between two measures related to (i) the count of IP addresses *successfully* reading a company's newly-published filings and (ii) the number of other firms whose newly-submitted reports the same IP addresses also *successfully* examine. A negative coefficient for this interaction term is consistent with the processing of other disclosures diverting scarce cognitive resources away from the integration of a particular firm's SEC reports.

This strategy is however subject to a number of endogeneity concerns. If the asset pricing implications of a firm's newly-published filings are vague, then IP addresses may decide to read other newly-submitted SEC reports afterward to receive more signals about the firm. That IP addresses consult other disclosures could be owing to unclear information contained in the company's reports, which then explains the negative relationship between the interaction term and price informativeness. Moreover, IP addresses may decide not to devote any effort to process a disclosure if it is either hard to interpret or inconsequential for stock prices. This frees up the investors' resources, allowing them to read more filings from other firms. Specifically, price informativeness being lower when IP addresses view other companies' filings may be a symptom of SEC reports' low readability or little relevance for firm value. Note that IP addresses do not need to actually view a firm's disclosures for these mechanisms to take effect. The expectation of ambiguous information content or poor legibility may also induce IP addresses to consult other firm's disclosures even before downloading a company's reports.

We deal with these concerns by once again leveraging the HTTPS policy implemented by the SEC website in a difference-in-differences design. We first show that what matters for price informativeness is not only IP addresses' intention to download other companies' disclosures, which may be owing to their anticipation of the quality of the information contained in a specific firm's filings, but their actual reading of the other reports as well. We build the variable $OthInd_{i,j,t}$ measuring the potential distraction at the information integration stage experienced by IP address j who tries to download firm i's reports on filing date t. It is defined as the number of firms not sharing the same industry as i that are likewise attempted to be viewed by j. Industries are according to Fama and French's (1997) 48-industry classification scheme. We do not include companies from the same industry as i since they may be a source of informative signals about the firm. We then take the mean of this variable over all IP addresses who have (i) a non-missing value for the exposure measure *ErrorExp* and (ii) a non-zero value for *OthInd*. Our firm-day-level proxy for distraction while IP addresses integrate information is the log of this average, denoted by *Log(OthInd)*.

Using a model similar to Equation (2), we regress the proxies for price informativeness on the interaction of *Log(OthInd)* and *Log(IPs3)*—the logged count of IP addresses attempting to view a company's newly-published filings who have non-missing values for the exposure and distraction variables. Finding a negative coefficient for this interaction is in line with the distraction hypothesis at the information integration stage. But since the results of this specification may be explained by IP addresses' expectation of information content, we subsequently consider the triple interaction of *Log(IPs3)*, *Log(OthInd)*, and *ErrorExp*. A negative coefficient for the interaction between *Log(IPs3)* and *Log(OthInd)*, and a positive coefficient for the triple interaction means that IP addresses attempting to process other reports decreases price informativeness, but more so if they are less exposed to unsuccessful redirections.

The coefficient estimates are reported in Panel A of Table 6. All the regressions control for the interaction of the intended news reading proxy with *Log(OwnInd)*, the same-industry analog of *Log(OthInd)*, and the logged counts of the number of firms in and out of a specific firm's industry that have newly-published filings on the report date (i.e., *Log(OthIndAll)* and *Log(OwnIndAll)*). The odd-numbered columns show the findings when the error exposure variable is suppressed from the regression specification. Consistent with the distraction hypothesis, stock prices are less informative if the IP addresses trying to download a firm's newly-published filings likewise attempt to access new reports submitted by companies belonging to other industries. In particular, a one-SD rise in the distraction variable diminishes the impact of *Log(IPs3)* on the percentage of CAR attributable to the report date by 43%, on the percentage of cumulative volume traded on the report date by 40%, and on abnormal idiosyncratic volatility by 47%.

We next consider the triple interaction in the even-numbered columns. As conjectured, the coefficients of the triple interaction are all positive and statistically significant. If error exposure increases by one SD, then the attenuation in the effect of intended news reading owing to a one-SD boost in *Log(OthInd)* is less pronounced. In this case, the decline in the impact of *Log(IPs3)* is instead 33% for *PctAR*, 31% for *PctVolume*, and 31% for *AbIdVol*.

In line with frictions at the information integration stage reducing price informativeness, the results show that actual views of newly-published filings of firms from other industries has an adverse impact on the outcome variables. These findings may however still be driven by IP addresses consulting other disclosures after successfully viewing an SEC report and realizing that it contains little information pertinent to firm value. We address this remaining concern by repeating the regressions employed in Panel A of Table 6, but this time defining potential distraction by only counting other-industry firms whose newly-submitted reports IP addresses try to consult *before* attempting to download any of a particular firm's disclosures. Our new distraction variable is *Log(OthIndBef)*. The coefficient estimates, displayed in Panel B, confirm that our previous conclusions remain valid. Successful reading of other companies' disclosures even before seeing a particular firm's reports impedes price informativeness.

7 Conclusion

In this study, we isolate frictions at the information acquisition and integration stages of information processing by leveraging a policy implemented by the SEC website that started automatically redirecting HTTP traffic to more secure HTTPS web pages. Some of these redirections failed, leading to some IP addresses being unable to download the company filings they had requested. We exploit this plausibly exogenous variation in news access in a difference-in-differences design to show that while a higher number of IP addresses attempting to view a firm's newly-published disclosures is positively associated with price informativeness, greater exposure of the IP addresses to unsuccessful redirections weakens this relationship. This is consistent with disruptions during information acquisition impairing the information content of stock prices. We assess the identifying assumptions of our empirical strategy and demonstrate (i) that there are no pre and post trends among firms with different exposures to unfulfilled requests, and (ii) that our findings are confirmed by placebo tests. Our baseline results are also not owing to IP addresses with higher exposure being less sophisticated and they survive a slew of robustness checks.

The second part of the paper disentangles the impact on price informativeness of frictions at the information integration step from those at the earlier two by once again leveraging the SEC website's HTTPS policy in a difference-in-differences design. Following the investor distraction literature, we measure potential distraction during information integration as the number of firms whose newly-disclosed reports are also attempted to be read by IP addresses who try to download a particular company's filings. Consistent with IP addresses having limited resources for information processing, we obtain that the positive association between price informativeness and the number of IP addresses requesting to consult a firm's new reports is moderated by the IP addresses' level of potential distraction. The mitigating effect of potential distraction is less pronounced if the IP addresses are more exposed to failed redirections. This implies that successful reading of other disclosures impairs price informativeness and not only the intention to do so, which may be owing to their anticipation of the quality of the information contained in a specific firm's filings. We also rule out that actual knowledge of information content is driving these results, as the successful viewing of other reports even *before* downloading a particular firm's disclosures likewise matters for the amount of information contained in filing-date prices.

Our study's findings provide strong empirical support for the three-step framework proposed by Blankespoor et al. (2019) and Blankespoor et al. (2020) for understanding investors' use of information. Our ability to observe individual IP addresses' intended and actual information sets, together with our leveraging of the natural experiment, allows us cleanly identify the impact of the acquisition and integration stages on price informativeness. Our setup is flexible enough to be employed by future work to investigate how the steps of information processing affect other market outcomes, like stock liquidity or return comovement.

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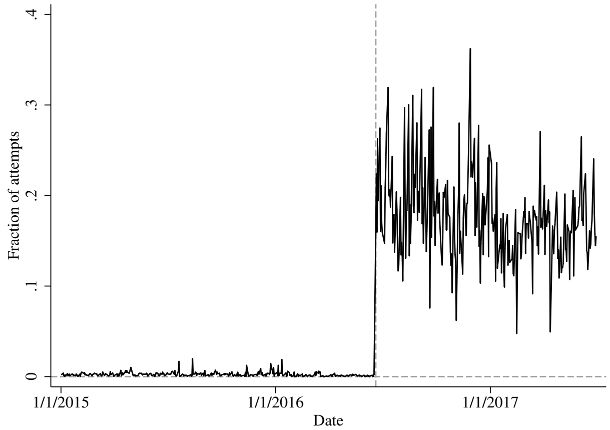
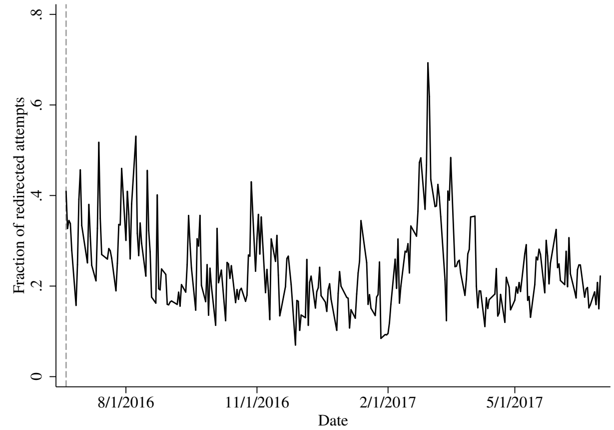
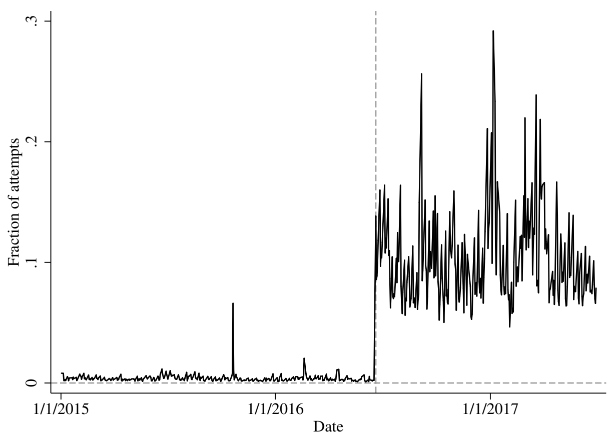


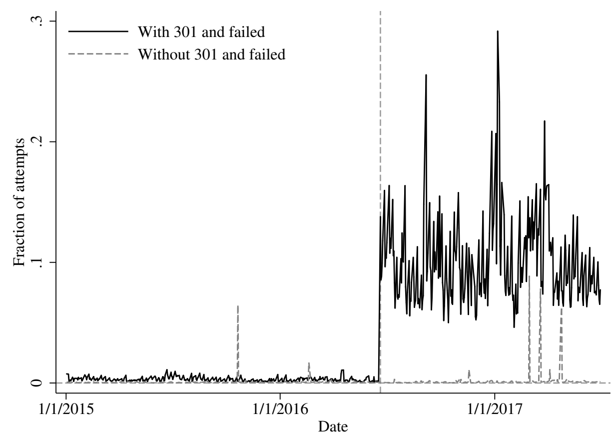
(a) Fraction of redirected attempts



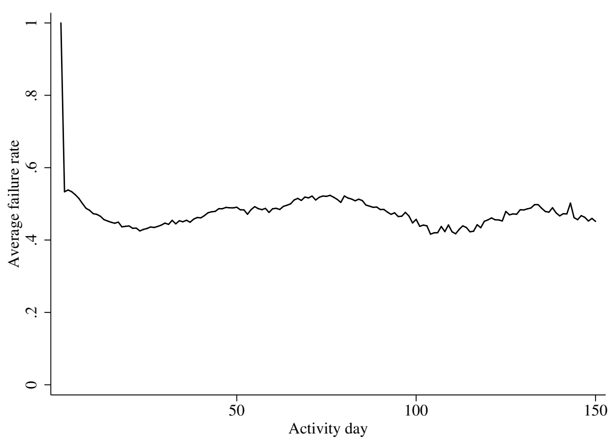
(b) Fraction of failed redirected attempts



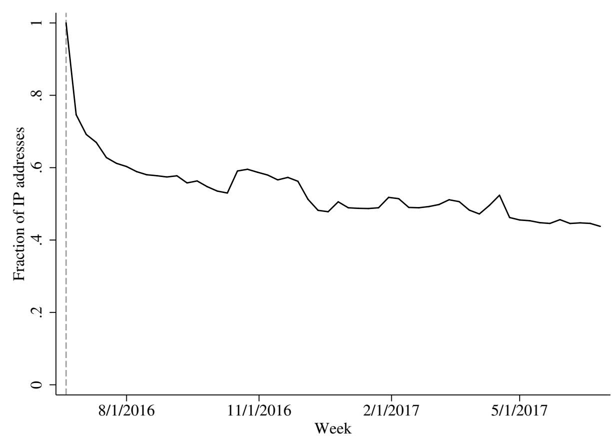
(c) Fraction of failed attempts



(d) Fraction of failed attempts by HTTPS Status Code

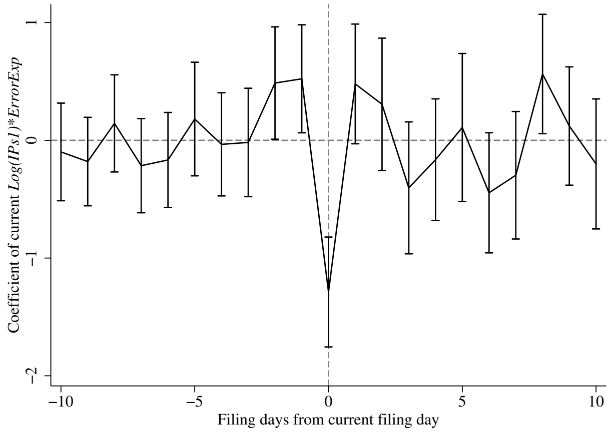


(e) Average failure rate across activity days

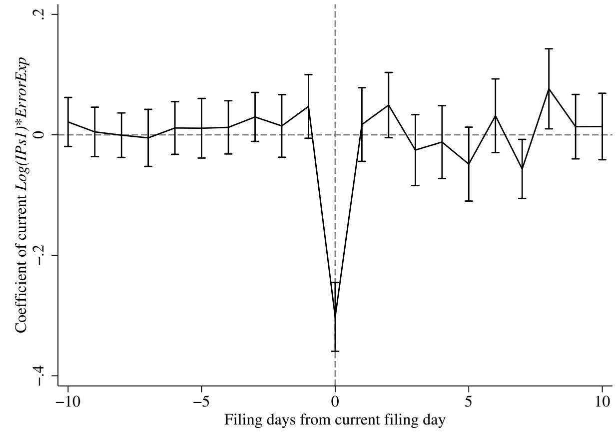


(f) Fraction of IP addresses with first activity

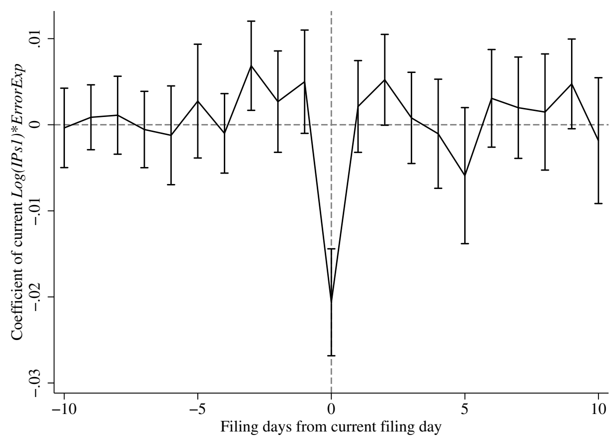
Figure 1: Effects of the HTTPS policy. Figure 1a plots the daily percentage of attempts to view a newly-published company report that are redirected on the filing date. An IP address is redirected if at least one of their visits registers an HTTP Status Code 301 ("Moved permanently") before the end of the trading day. The dashed vertical gray line indicates the day when the SEC starts automatically redirecting HTTP traffic to HTTPS (i.e., June 20, 2016). Figure 1b reports the percentage of redirected attempts to download newly-published filings that are not successful. An IP address successfully downloads an SEC report if at least one of their visits registers an HTTP status code between 200 and 226 ("Successful") before the end of the trading day. Figure 1c plots the daily fraction of unsuccessful attempts to access *any* filing (i.e., both newly-published and previously-published). In Figure 1d, the fraction of failed attempts is further broken down into those that register an HTTP Status Code 301 and other codes. The other codes include HTTP Status Code 400 ("Bad request"), 403 ("Forbidden"), 429 ("Too many requests"), 500 ("Internal server error"), 502 ("Bad gateway"), 503 ("Service unavailable"), and 504 ("Gateway timeout"). Figure 1e considers IP addresses whose attempts to view any filing are all redirected and unsuccessful on the first day after June 19, 2016, they are active on EDGAR. Here, we plot the average across IP addresses of the fraction of attempts that are both redirected and unsuccessful in the next activity days following the first. For each week starting June 20, 2016, we report in Figure 1f the ratio between the number of IP addresses whose first activity after the policy is during a specific week and the number of all active IP addresses during the week.



(a) Abnormal return as percentage of 31-day CAR

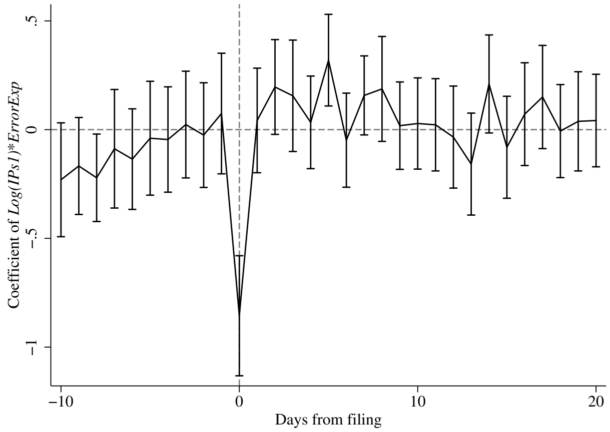


(b) Volume as percentage of 31-day cumulative volume

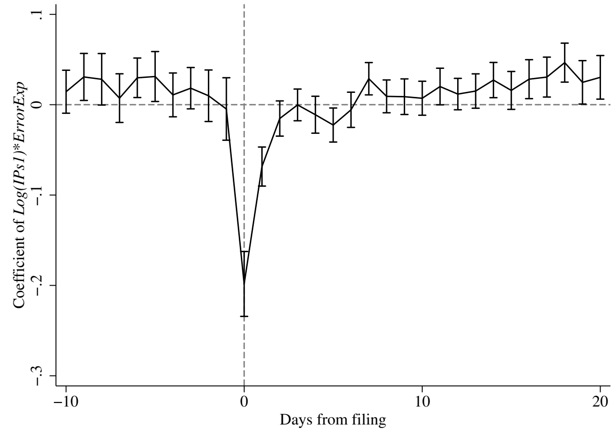


(c) Abnormal idiosyncratic volatility

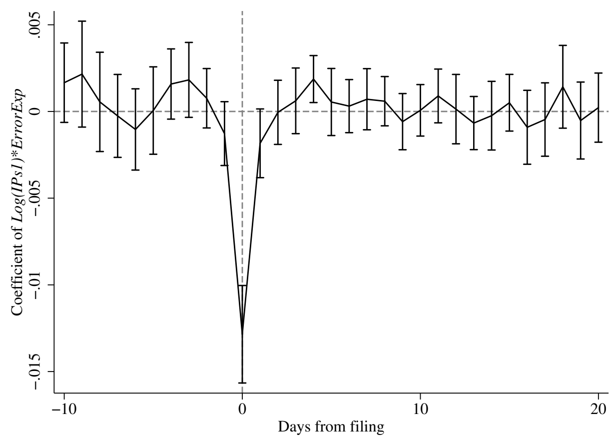
Figure 2: Event-time trends before and after exposure to unsuccessful redirections. The figure contains estimates from the regression in Equation (3). The sample period is from October 1, 2015, to March 8, 2017. *Log(IPs1)* is standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. The title of each panel is the dependent variable in the regressions. All variables are defined in Table 1. For t' from -10 to 10, the panels display the estimates for $\eta_{t'}$. Standard errors used for the 95% confidence intervals, shown as vertical bars around the point estimates, are two-way clustered at the firm and trading day levels.



(a) Abnormal return as percentage of 31-day CAR



(b) Volume as percentage of 31-day cumulative volume



(c) Abnormal idiosyncratic volatility

Figure 3: Calendar-time trends before and after exposure to unsuccessful redirections. The figure contains estimates from the regression in Equation (4). The sample period is from October 1, 2015, to March 8, 2017. *Log(IPs1)* is standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. The title of each panel is the dependent variable in the regressions. All variables are defined in Table 1. For s' from -10 to 20, the panels display the estimates for $\theta_{s'}$. Standard errors used for the 95% confidence intervals, shown as vertical bars around the point estimates, are two-way clustered at the firm and trading day levels.

Table 1: Variable definitions and summary statistics. Panel A lists the variables used in the empirical analysis, together with their definitions. Panel B shows the summary statistics for the 68,349 firm-filing date pairs (3,110 unique firms, 361 unique dates, and 149,851 unique filings) that constitute the final sample. The sample period is from October 1, 2015, to March 8, 2017.

Panel A: Variable definitions

Variable	Definition
Log(IPs0)	Logged number of unique IP addresses attempting to view a filing submitted on date t
Log(IPs1)	Logged number of unique IP addresses attempting to view a filing on t who access disclosures published before t
ErrorExp	Average failure rate of IP addresses trying to view a filing on t; IP-level failure rate is the percentage of attempts on t to consult disclosures published before t that are not successful and register HTTP Status Code 301; set to zero before June 20, 2016
PctAR	CAPM alpha divided by $CAR^{-10,20}$; CAR^{T_1,T_2} is the cumulative CAPM alpha from $t+T_1$ to $t+T_2$, where the beta is estimated from $t-70$ to $t-10$
PctVolume	Trading volume divided by cumulative volume from $t-10$ to $t+20$
AbIdVol	Daily idiosyncratic volatility minus the average daily idiosyncratic volatility from $t-30$ to $t-11$; idiosyncratic volatility is the standard deviation of the residuals from a regression of 5-minute returns on 5-minute market returns
Log(OthIPs1)	*Log(IPs0)* minus *Log(IPs1)*
PctARPre	$CAR^{-10,-1}$ divided by $CAR^{-10,20}$
CAR	$CAR^{-10,20}$
AbsCAR	Absolute value of $CAR^{-10,20}$
PctInst	Fraction of shares held by institutions based on their most recent 13-F filing, as of $t-10$
Log(Analysts)	Log of one plus the number of analysts in the previous month reporting forecasts of a stock's EPS for the current quarter, as of $t-10$
I(Friday)	Dummy variable for filings made public on Fridays or on days before holidays
Log(MktCap)	Logged market capitalization; market capitalization is previous daily closing price times the previous number of shares outstanding, as of $t-10$
MTB	Market capitalization divided by the book value of common equity for the most recently concluded quarter, as of $t-10$
MOM	Cumulative daily raw return from $t-260$ to $t-11$
I(Insiders)	Dummy variable for firm-days with SEC Forms 3 or 4, including amendments
I(Current)	Dummy variable for firm-days with SEC Form 8-K, including amendments
I(Periodic)	Dummy variable for firm-days with SEC Forms 10-Q or 10-K, including amendments
I(Proxy)	Dummy variable for firm-days with SEC Forms DEF 14A or DEFA14A, including amendments
I(Earnings)	Dummy variable for firm-days with earnings announcements (EAs); value is also 1 for the day after EAs
Log(NFilings)	Logged number of company reports filed on t
Illiq	Amihud's (2002) illiquidity measure, as of $t-10$
Vol	Standard deviation of daily returns from $t-70$ to $t-11$
Log(FileSize)	Log of the sum of the file sizes in bytes of a firm's SEC filings on t
RMSDOwnPre	Root mean squared deviation (RMSD) of analysts' estimates of the firm's EPS at the end of the submission date from the analysts' own estimate right before the publication of the first SEC filing on t; normalized by stock price at $t-11$
RMSDMedPreCh	RMSD of estimates at the end of the submission date minus RMSD of estimates right before the publication of the first SEC filing on t; deviations are calculated from the median estimate right before the publication of the first SEC filing on t; normalized by stock price at $t-11$

(Continued)

Table 1–*Continued*

Variable	Definition
RMSDOwnFutCh	RMSD of estimates at the end of the submission date minus RMSD of estimates right before the publication of the first SEC filing on t; deviations are calculated from the analysts' own estimate 20 days after t; normalized by stock price at $t-11$
RMSDMedFutCh	RMSD of estimates at the end of the submission date minus RMSD of estimates right before the publication of the first SEC filing on t; deviations are calculated from the median estimate 20 days after t; normalized by stock price at $t-11$
TotErrorExp	Average total failure rate of IP addresses trying to view a filing on t; IP-level total failure rate is the percentage of attempts from June 20, 2016, to March 8, 2017, to consult disclosures not published on the date of the attempt that are not successful and register HTTP Status Code 301
Log(IPs2)	Logged number of unique IP addresses attempting to view a filing on t who have a non-missing value for *ErrorExp* and *TotErrorExp*
Log(OthIPs2)	*Log(IPs1)* minus *Log(IPs2)*
Log(OthInd)	Logged average number of firms from other industries whose newly-published SEC reports are attempted to be read by IP addresses trying to view a company's filing on t
Log(OwnInd)	Logged average number of firms from the same industry whose newly-published SEC reports are attempted to be read by IP addresses trying to view a company's filing on t
Log(OthIndAll)	Logged number of firms from other industries that publish an SEC report on t
Log(OwnIndAll)	Logged number of firms from the same industry that publish an SEC report on t
Log(IPs3)	Logged number of unique IP addresses attempting to view a filing on t (1) who have a non-missing value for *ErrorExp* and (2) who try to download at least one newly-published SEC report of a firm from another industry
Log(OthIPs3)	*Log(IPs1)* minus *Log(IPs3)*
Log(OthIndBef)	Logged average number of firms from other industries whose newly-published SEC reports are attempted to be read before IP addresses try to view a company's filing on t
Log(OwnIndBef)	Logged average number of firms from the same industry whose newly-published SEC reports are attempted to be read before IP addresses try to view a company's filing on t
Log(OthIndAllBef)	Logged number of firms from other industries that publish an SEC report before a company's first filing on t
Log(OwnIndAllBef)	Logged number of firms from the same industry that publish an SEC report before a company's first filing on t

Panel B: Summary statistics

Variable	Count	Mean	Median	Standard deviation	Minimum	Maximum
IPs0	68,349	16.020	8	69.146	1	10,567
IPs1	68,349	11.855	6	37.149	1	8,085
ErrorExp post-policy	32,182	0.068	0	0.146	0	1
PctAR	68,349	0.068	0.035	0.295	-0.827	1.187
PctVolume	68,349	0.041	0.031	0.033	0.006	0.205
AbIdVol in %	11,832	0.047	-0.002	0.179	-0.174	0.983
PctARPre	68,349	0.362	0.337	0.587	-1.378	2.168
CAR	68,349	0.003	0.053	0.154	-0.403	0.373
AbsCAR	68,349	0.134	0.108	0.082	0.051	0.457
PctInst	68,349	0.757	0.809	0.266	0.060	1.344
Analysts	68,349	9.074	7	7.967	0	35
I(Friday)	68,349	0.196	0	0.397	0	1
MktCap in billions	68,349	7.752	1.108	23.781	0.027	175.959

(Continued)

Table 1–*Continued*

Variable	Count	Mean	Median	Standard deviation	Minimum	Maximum
MTB	68,349	4.222	2.293	6.992	0.350	53.832
MOM	68,349	0.041	-0.010	0.472	-0.769	2.237
I(Insiders)	68,349	0.457	0	0.498	0	1
I(Current)	68,349	0.375	0	0.484	0	1
I(Periodic)	68,349	0.121	0	0.326	0	1
I(Proxy)	68,349	0.032	0	0.176	0	1
I(Earnings)	68,349	0.151	0	0.358	0	1
NFilings	68,349	2.141	1	2.292	1	13
Illiq in %	68,349	0.062	0.002	0.264	0.000	2.136
Vol in %	68,349	2.493	2.289	1.020	0.883	5.429
FileSize in megabytes	68,349	1.985	0.060	5.075	0.004	31.035
RMSDOwnPre in %	62,839	0.031	0	0.122	0	0.903
RMSDMedPreCh in %	62,839	0.009	0	0.052	-0.048	0.420
RMSDOwnFutCh in %	62,839	-0.021	0	0.094	-0.717	0.000
RMSDMedFutCh in %	62,839	-0.011	0	0.057	-0.457	0.019
TotErrorExp	64,365	0.077	0.001	0.159	0	1
IPs2	64,365	10.349	5	37.083	1	8,085
OthInd	64,157	7.139	6.200	4.734	1	55
OwnInd	64,157	1.636	1.250	1.024	1	22
OthIndAll	64,157	595.410	548	259.668	140	1,992
OwnIndAll	64,157	40.732	26	39.482	1	377
IPs3	64,157	7.804	4	12.638	1	363
OthIndBef	59,164	4.430	3.600	3.367	1	51
OwnIndBef	59,164	1.377	1.000	0.714	1	16
OthIndAllBef	59,164	229.189	204	165.789	1	1,315
OwnIndAllBef	59,164	16.598	9	20.025	1	237

Table 2: Exposure to unsuccessful redirections and price informativeness. This table reports the estimates from panel regressions of three variables associated with price informativeness on the interaction between the logged number of IP addresses attempting to download a filing—*Log(IPs1)*—and a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections. All variables are defined in Table 1. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The *t*-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		−0.590***		−0.155***		−0.008***
		(−3.63)		(−9.93)		(−5.72)
Log(IPs1)	1.599***	1.701***	0.596***	0.622***	0.023***	0.025***
	(9.64)	(10.01)	(27.41)	(27.18)	(10.46)	(10.64)
ErrorExp		−0.534***		−0.176***		−0.008***
		(−2.65)		(−8.25)		(−4.27)
Log(OthIPs1)	0.397***	0.398***	0.140***	0.138***	0.006***	0.006***
	(3.14)	(3.15)	(11.88)	(11.81)	(4.06)	(3.97)
PctARPre	−6.011***	−6.015***	0.034**	0.032**	−0.004**	−0.004**
	(−26.44)	(−26.45)	(2.58)	(2.50)	(−2.18)	(−2.23)
CAR	0.249	0.250	−0.034*	−0.034*	−0.009***	−0.009***
	(1.21)	(1.21)	(−1.96)	(−1.94)	(−4.97)	(−5.00)
AbsCAR	−0.384***	−0.385***	0.028*	0.027*	0.013***	0.013***
	(−2.68)	(−2.69)	(1.94)	(1.92)	(6.47)	(6.47)
PctInst	0.403	0.400	0.026	0.025	0.003	0.003
	(0.94)	(0.93)	(0.65)	(0.64)	(0.60)	(0.61)
Log(Analysts)	0.685	0.689	0.182***	0.184***	−0.007	−0.008
	(1.17)	(1.17)	(2.71)	(2.74)	(−1.23)	(−1.36)
I(Friday)	−0.536***	−0.530***	−0.149***	−0.147***	−0.006***	−0.006***
	(−3.10)	(−3.06)	(−6.36)	(−6.30)	(−3.12)	(−3.09)
Log(MktCap)	0.535	0.508	0.003	0.000	−0.054***	−0.053***
	(0.34)	(0.32)	(0.02)	(0.00)	(−2.65)	(−2.61)
MTB	0.098	0.095	0.018	0.017	−0.000	−0.000
	(0.33)	(0.32)	(0.48)	(0.45)	(−0.05)	(−0.10)
MOM	−0.111	−0.114	−0.010	−0.011	−0.001	−0.001
	(−0.50)	(−0.51)	(−0.45)	(−0.48)	(−0.34)	(−0.43)
I(Insiders)	−0.714***	−0.704***	−0.190***	−0.185***	−0.004**	−0.004*
	(−3.41)	(−3.36)	(−8.47)	(−8.29)	(−2.03)	(−1.90)
I(Current)	0.893***	0.868***	0.144***	0.136***	0.013***	0.013***
	(5.01)	(4.85)	(7.40)	(6.95)	(6.68)	(6.43)
I(Periodic)	−1.023	−1.011	−0.307***	−0.302***	−0.007	−0.008
	(−1.57)	(−1.55)	(−4.25)	(−4.17)	(−0.76)	(−0.77)
I(Proxy)	−0.343**	−0.342**	−0.020	−0.020	−0.004*	−0.004*

(Continued)

Table 2–*Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
	(−2.07)	(−2.07)	(−0.79)	(−0.80)	(−1.69)	(−1.68)
I(Earnings)	5.454***	5.445***	1.130***	1.127***	0.090***	0.090***
	(21.98)	(21.94)	(38.43)	(38.45)	(23.58)	(23.57)
Log(NFilings)	−0.052	−0.043	−0.029	−0.026	−0.006***	−0.006***
	(−0.35)	(−0.28)	(−1.60)	(−1.40)	(−3.16)	(−3.05)
Illiq	−0.312	−0.318	0.057	0.056	0.001	0.000
	(−0.93)	(−0.95)	(1.56)	(1.53)	(0.15)	(0.04)
Vol	−0.527*	−0.540*	−0.070**	−0.073**	−0.022***	−0.022***
	(−1.69)	(−1.73)	(−2.22)	(−2.32)	(−5.39)	(−5.48)
Log(FileSize)	0.582**	0.572**	0.093***	0.090***	0.002	0.002
	(2.26)	(2.23)	(2.91)	(2.81)	(0.63)	(0.55)
Log(FileSize)×I(Insiders)	0.310*	0.307*	−0.007	−0.009	0.001	0.001
	(1.71)	(1.70)	(−0.35)	(−0.48)	(0.74)	(0.75)
Log(FileSize)×I(Current)	1.134***	1.130***	0.235***	0.234***	0.006**	0.006**
	(6.02)	(6.00)	(10.75)	(10.66)	(2.18)	(2.25)
Log(FileSize)×I(Periodic)	0.240	0.264	0.030	0.037	−0.003	−0.002
	(0.63)	(0.70)	(0.77)	(0.95)	(−0.54)	(−0.49)
Log(FileSize)×I(Proxy)	0.223	0.220	0.016	0.015	0.001	0.001
	(1.33)	(1.32)	(0.68)	(0.66)	(0.76)	(0.73)
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	68,349	68,349	68,349	68,349	11,832	11,832
Adjusted R^2	0.119	0.119	0.291	0.291	0.485	0.486

Table 3: Exposure to unsuccessful redirections and intended news reading of dropped IP addresses. This table reports the estimates from panel regressions of three variables associated with price informativeness on the interaction between the logged counts of IP addresses attempting to download a filing—*Log(IPs1)* and *Log(IPs0 − IPs1)*—and a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections. The controls are as in Table 2 with the exception of *Log(OthIPs1)*, which is excluded. All variables are defined in Table 1. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		-0.478^{**}		-0.103^{***}		-0.003^{**}
		(−2.36)		(−5.06)		(−2.00)
Log(IPs0 − IPs1)×ErrorExp		0.299		−0.045		−0.005
		(0.93)		(−1.42)		(−1.57)
Log(IPs1)	1.440^{***}	1.532^{***}	0.575^{***}	0.593^{***}	0.017^{***}	0.017^{***}
	(6.48)	(6.71)	(20.80)	(20.64)	(5.94)	(6.09)
Log(IPs0 − IPs1)	1.097^{***}	1.038^{***}	0.325^{***}	0.327^{***}	0.016^{***}	0.017^{***}
	(5.05)	(4.56)	(12.77)	(12.40)	(5.35)	(5.17)
ErrorExp		−0.221		-0.165^{***}		-0.009^{***}
		(−0.80)		(−6.02)		(−3.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,605	43,605	43,605	43,605	8,233	8,233
Adjusted R^2	0.128	0.128	0.304	0.304	0.495	0.495

Table 4: Exposure to unsuccessful redirections and analyst estimate revisions. This table reports the estimates from panel regressions of four variables related to report-date revisions of analyst estimates of a firm's EPS on the interaction between the logged number of IP addresses attempting to download a filing—*Log(IPs1)*—and a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections. The controls are as in Table 2. All variables are defined in Table 1. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable (in %)							
	RMSDOwnPre		RMSDMedPreCh		RMSDOwnFutCh		RMSDMedFutCh	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(IPs1)×ErrorExp		−0.000		−0.000		−0.000		−0.000
		(−0.71)		(−0.28)		(−0.04)		(−0.20)
Log(IPs1)	0.002***	0.002***	0.000	0.000	−0.001	−0.001	−0.000	−0.000
	(2.78)	(2.90)	(1.55)	(1.59)	(−1.59)	(−1.63)	(−0.97)	(−0.99)
ErrorExp		0.001		0.000		−0.001*		−0.001*
		(1.63)		(0.95)		(−1.93)		(−1.81)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62,839	62,839	62,839	62,839	62,839	62,839	62,839	62,839
Adjusted R^2	0.279	0.279	0.162	0.162	0.256	0.256	0.206	0.206

Table 5: Controlling for average error exposure after HTTPS policy. This table reports the estimates from panel regressions of three variables associated with price informativeness on the interaction of the logged number of IP addresses attempting to download a filing—*Log(IPs2)*—with the proxies *ErrorExp* and *TotErrorExp* for the exposure of the IP addresses to unsuccessful redirections. The regressions likewise include *Log(OthIPs1)* and *Log(OthIPs2)* to account for IP addresses dropped from the definition of *Log(IPs2)*. The remaining controls are as in Table 2. All variables are defined in Table 1. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp* and *TotErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016, while *TotErrorExp* has unit standard deviation for the whole sample period. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs2)×ErrorExp	−0.702***	−0.485**	−0.180***	−0.067***	−0.009***	−0.007***
	(−4.11)	(−2.25)	(−10.68)	(−3.21)	(−5.82)	(−2.68)
Log(IPs2)×TotErrorExp		−0.303*		−0.157***		−0.003
		(−1.73)		(−8.99)		(−1.31)
Log(IPs2)	2.000***	2.067***	0.712***	0.747***	0.027***	0.028***
	(10.66)	(10.63)	(27.39)	(28.10)	(9.99)	(10.09)
ErrorExp	−0.552***	−0.194	−0.172***	−0.029	−0.008***	−0.005
	(−2.98)	(−0.76)	(−8.57)	(−1.18)	(−4.31)	(−1.58)
TotErrorExp		−0.470**		−0.189***		−0.003
		(−2.11)		(−9.41)		(−0.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,365	64,365	64,365	64,365	11,272	11,272
Adjusted R^2	0.121	0.121	0.294	0.295	0.489	0.489

Table 6: Reading of filings from other industries and price informativeness. Panel A reports the estimates from panel regressions of three variables associated with price informativeness on the triple interaction of the logged number of IP addresses trying to download a filing (*Log(IPs3)*), the logged average number of firms from other industries whose newly-published filings are also attempted to be viewed by the IP addresses (*Log(OthInd)*), and a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections. The regressions control for the interaction terms of *Log(IPs3)* with *Log(OwnInd)*, *Log(OthIndAll)*, and *Log(OwnIndAll)*. Other regressors are *Log(OthIPs1)* and *Log(OthIPs3)* to account for the dropped IP addresses from the definition of *Log(IPs3)*. The remaining controls are as in Table 2. All variables are defined in Table 1. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. In Panel B, *Log(OthInd)* is replaced with its counterpart, *Log(OthIndBef)*, that only counts attempted queries to other firms' reports that occur before an IP address' first intention to download a company's filing. The regressions control for the interaction terms of *Log(IPs3)* with *Log(OwnIndBef)*, *Log(OthIndAllBef)*, and *Log(OwnIndAllBef)*. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: All attempts to view filings of firms from other industries

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs3)×Log(OthInd)×ErrorExp		0.299^{**}		0.083^{***}		0.006^{***}
		(1.98)		(5.63)		(3.45)
Log(IPs3)×ErrorExp		-0.496^{**}		-0.088^{***}		-0.006^{***}
		(−2.57)		(−4.12)		(−2.84)
Log(IPs3)×Log(OthInd)	-0.608^{***}	-0.620^{***}	-0.223^{***}	-0.233^{***}	-0.009^{***}	-0.010^{***}
	(−4.40)	(−4.29)	(−13.99)	(−13.84)	(−5.39)	(−5.27)
Log(IPs3)	1.409^{***}	1.479^{***}	0.558^{***}	0.567^{***}	0.019^{***}	0.019^{***}
	(8.44)	(8.64)	(26.55)	(25.90)	(8.90)	(8.77)
ErrorExp		-0.480^{*}		-0.131^{***}		-0.009^{***}
		(−1.92)		(−5.19)		(−3.22)
Log(OthInd)×ErrorExp		0.452^{**}		0.125^{***}		0.010^{***}
		(2.17)		(6.50)		(3.99)
Log(OthInd)	-0.591^{***}	-0.653^{***}	-0.239^{***}	-0.257^{***}	-0.012^{***}	-0.013^{***}
	(−3.68)	(−3.78)	(−12.30)	(−12.31)	(−5.30)	(−5.52)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64,157	64,157	64,157	64,157	11,133	11,133
Adjusted R^2	0.124	0.124	0.300	0.301	0.495	0.495

(Continued)

Table 6–*Continued*

Panel B: Prior attempts to view filings of firms from other industries

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs3)×Log(OthIndBef)×ErrorExp		0.293*		0.074***		0.005***
		(1.77)		(4.61)		(3.81)
Log(IPs3)×ErrorExp		−0.503**		−0.101***		−0.004*
		(−2.25)		(−4.52)		(−1.96)
Log(IPs3)×Log(OthIndBef)	−0.388***	−0.393***	−0.158***	−0.164***	−0.006***	−0.007***
	(−2.73)	(−2.61)	(−9.10)	(−8.88)	(−3.84)	(−3.95)
Log(IPs3)	1.525***	1.603***	0.581***	0.594***	0.019***	0.019***
	(8.46)	(8.59)	(25.59)	(25.01)	(8.52)	(8.26)
ErrorExp		−0.438*		−0.109***		−0.005*
		(−1.80)		(−4.22)		(−1.92)
Log(OthIndBef)×ErrorExp		0.475**		0.110***		0.008***
		(2.29)		(5.49)		(4.31)
Log(OthIndBef)	−0.361**	−0.445***	−0.156***	−0.175***	−0.008***	−0.009***
	(−2.40)	(−2.71)	(−8.57)	(−8.86)	(−3.89)	(−4.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,164	59,164	59,164	59,164	10,450	10,450
Adjusted R^2	0.125	0.125	0.298	0.299	0.496	0.496

Online Appendix to "Information Processing Frictions and Price Informativeness: Evidence from a Natural Experiment"

OA.1 Steps for adherence to HTTPS-Only Standard

Adherence to the HTTPS-Only Standard comprises three steps. First, services by Federal websites must be available using an HTTPS connection. Second, HTTP requests must be either redirected automatically to HTTPS or disabled completely. Allowing HTTP connections solely to redirect traffic to HTTPS is however encouraged. Third, HTTP Strict Transport Security (HSTS) must be in force. HSTS addresses the problem that the redirect from HTTP to HTTPS is still insecure. An HSTS policy ensures that HTTPS is used even when an HTTP link is clicked or an address without a specified protocol is typed in the browser. One drawback is that HSTS only takes effect after the first successful secured connection to a specific domain. To maximize the protection offered by HSTS, websites can apply to be included in an "HSTS preload list." This is composed of domains for whom the most common web browsers, like Chrome, enable HSTS even for the first visit.

OA.2 Determining the start of automatic redirections from HTTP to HTTPS

The SEC did not announce when its website started following the memorandum. Nonetheless, the council of Federal Chief Information Officers reported on the compliance of government agencies to the HTTPS-Only Standard through a public dashboard. It used to be available online at https://pulse.cio.gov but is now inaccessible. We consult a digital archive of this website and search for the dates when the SEC met the requirements of the policy.[1] Since historical snapshots of the dashboard are missing for some days, we are only able to obtain time intervals for the compliance milestones of the SEC. The SEC started automatically redirecting HTTP traffic to HTTPS between June 3, 2016, and October 7, 2016, and using HSTS between January 11, 2017, and January 30, 2017. As of August 2, 2017, the SEC domain had still not been added to the preload list.

We can further narrow down the period during which the SEC implemented the second phase

[1] We use the Wayback Machine (https://web.archive.org) to determine how the website looked in the past.

of the HTTPS-Only Standard. Checking the digital archive of www.sec.gov (i.e., without the protocol), one is led to http://www.sec.gov as late as June 19, 2016, and to https://www.sec.gov as early as June 23, 2016. This implies that automatic redirections from HTTP to HTTPS began in between these two dates.

OA.3 Other potential causes of failed redirections

The client's operating system may also be permitting outgoing traffic from port 80 (i.e., the port for HTTP traffic), which allows the client to send the first request, but not from port 443 (i.e., the port for HTTPS traffic). That is, clients may be barred from connecting through HTTPS. With the almost universal adoption of HTTPS nowadays, it is currently commonplace to leave port 443 unblocked. However, according to the HTTP Archive, only around 36% of the requests to the 500,000 web pages they crawled in December 2016 were through HTTPS.[2] At that point in time, some system administrators might have decided to disable HTTPS traffic since HTTP was the prevalent protocol anyway and blocking unused ports is a good security measure to prevent cyber attacks. Finally, a client may not be redirected to the HTTPS address because the internet connection is lost in between receiving the code 301 and making the follow-up request.

OA.4 Construction of control variables

The values of the following control variables are taken ten days before the filing date (i.e., on $t-10$). The percentage of institutional ownership (*PctInst*) is the fraction of shares outstanding held by institutions according to their 13-F filing for the most recently concluded quarter. Analyst coverage (*Log(Analysts)*) is the logarithm of 1 plus the number of analysts in the previous month who report forecasts of a stock's EPS for the current quarter (i.e., an I/B/E/S forecast period indicator value of 6). Log market capitalization (*Log(MktCap)*) is the logarithm of the product of the lagged daily closing price and the lagged number of shares outstanding. The market-to-book ratio (*MTB*) is market capitalization divided by the book value of common equity for the most recently

[2] See https://httparchive.org/reports/state-of-the-web.

concluded quarter. We define momentum (*MOM*) on day $t-10$ as a stock's cumulative daily return from $t-260$ to $t-11$. Stock i's illiquidity is proxied by the illiquidity measure of Amihud (2002):

$$\text{Illiq}_{i,t-10} = \frac{10^8}{|D_{i,t-10}|} \sum_{t' \in D_{i,t-10}} \frac{|R_{i,t'}|}{dvol_{i,t'}}, \tag{OA.1}$$

where $R_{i,t'}$ is the return on day t', $dvol_{i,t'}$ the dollar volume traded, and $D_{i,t-10}$ the set of days from $t-70$ to $t-11$ with positive $dvol_{i,t'}$. Return volatility (*Vol*) is the standard deviation of the daily returns from $t-70$ to $t-11$.

We take the information content of SEC reports into account by appending to the list of controls indicator variables for five of the most commonly submitted types of disclosures, together with the level and the absolute value of $CAR^{-10,20}$. The dummies are *I(Insiders)* for firm-days with reports that disclose the trading activity of company insiders (e.g., Forms 3 or 4), *I(Current)* for firm-days with current reports (e.g., Form 8-K), *I(Periodic)* for firm-days with periodic reports (e.g., Forms 10-Q or 10-K), *I(Proxy)* for firm-days when proxy statements are published (e.g., Forms DEF 14A or DEFA14A), and *I(Earnings)* for firm-days that coincide with an earnings announcement. As seen in Table OA.1, 82.5% of all SEC reports filed during the sample period are either Forms 3, 4, 8-K, 10-Q, 10-K, DEF 4A, or DEFA14A. Moreover, 87.6% of all firm-days in the final sample have at least one of the aforementioned filing types. We do not have the announcement time for all earnings announcements, as this information is not available in Compustat. To address the possibility that earnings news is made public after trading hours, we consider the day after the recorded announcement date as also having an earnings announcement. We likewise control for *Log(NFilings)*, the logged number of reports filed on t, and pre-filing cumulative abnormal return $CAR^{-10,-1}$ as a fraction of the long-term price response. The latter is included as a regressor to account for information potentially being disclosed even before the reports' submission to the SEC (Ben-Rephael et al., 2020; Weller, 2018).

DellaVigna and Pollet (2009) show that investors are more distracted on Fridays, affecting information acquisition and hence price informativeness. We take this documented effect into account through the dummy *I(Friday)* for Fridays or days before holidays. Following Loughran and McDonald (2014), we control for the readability of the company report by including the variable *Log(FileSize)*, the logged size of the submission file in kilobytes. Quarterly and annual reports, which disclose firms' financial statements and contain numerous exhibits, are usually longer than 8-K filings. To account for differences in file sizes across filing types, we further interact *Log(FileSize)* with the dummies for the four report categories in the regressions.

OA.5 Construction of analyst revision variables

For each firm i, filing date t, forecast period end date t^e, and horizon h, let $\mathcal{A}_{i,t,t^e,h}$ be the set of analysts who on t have active estimates of i's EPS for horizon h ending on t^e. Horizon can either be A (annual) or Q (quarterly). Define the root mean square deviation (RMSD) of an analyst's own estimate post-filing from their own estimate pre-filing for forecast period end date t^e and horizon h as

$$\text{RMSDOwnPre}_{i,t,t^e,h} = \sqrt{\frac{1}{|\mathcal{A}_{i,t,t^e,h}|}\sum_{a\in\mathcal{A}_{i,t,t^e,h}}\left[e^{Post}(a,i,t,t^e,h)-e^{Pre}(a,i,t,t^e,h)\right]^2}, \tag{OA.2}$$

where $e^{Post}(a,i,t,t^e,h)$ is analyst a's estimate of EPS on t at 4 PM and $e^{Pre}(a,i,t,t^e,h)$ is their own estimate at the acceptance time of the earliest filing on t. The first dependent variable is then

$$\text{RMSDOwnPre}_{i,t} = \frac{1}{p_{i,t-11}}\frac{1}{|\mathcal{P}_{i,t}|}\left(\sum_{t^e\in\mathcal{T}^e_{i,t,\text{Q}}}\text{RMSDOwnPre}_{i,t,t^e,\text{Q}}+\frac{1}{4}\sum_{t^e\in\mathcal{T}^e_{i,t,\text{A}}}\text{RMSDOwnPre}_{i,t,t^e,\text{A}}\right), \tag{OA.3}$$

where $\mathcal{T}^e_{i,t,h}$ is the set of forecast period end dates with horizon h, $\mathcal{P}_{i,t}$ is the set of pairs of forecast period end dates and horizons (i.e., $|\mathcal{P}_{i,t}|$ is equal to the sum of $|\mathcal{T}^e_{i,t,\text{Q}}|$ and $|\mathcal{T}^e_{i,t,\text{A}}|$), and $p_{i,t-11}$ is the stock price at $t-11$. In other words, $RMSDOwnPre_{i,t}$ is the RMSD averaged across all forecast period end dates and horizons and normalized by the stock price 11 days before the report date. We divide annual $RMSDOwnPre_{i,t,t^e,\text{A}}$ by 4 to make it comparable with quarterly $RMSDOwnPre_{i,t,t^e,\text{Q}}$.

The outcome variable $RMSDMedPreCh_{i,t}$ is calculated as $RMSDMedPre^{Post}_{i,t}$, the average RMSD post-filing, minus $RMSDMedPre^{Pre}_{i,t}$, the average RMSD pre-filing. Both are similarly defined as $RMSDOwnPre_{i,t}$ in Equation (OA.3). However, this time, the RMSDs for forecast period end date t^e and horizon h are computed as

$$\text{RMSDMedPre}^{Post}_{i,t,t^e,h} = \sqrt{\frac{1}{|\mathcal{A}_{i,t,t^e,h}|} \sum_{a \in \mathcal{A}_{i,t,t^e,h}} \left[e^{Post}(a,i,t,t^e,h) - \bar{e}^{Pre}(i,t,t^e,h)\right]^2} \quad \text{and}$$
$$\text{RMSDMedPre}^{Pre}_{i,t,t^e,h} = \sqrt{\frac{1}{|\mathcal{A}_{i,t,t^e,h}|} \sum_{a \in \mathcal{A}_{i,t,t^e,h}} \left[e^{Pre}(a,i,t,t^e,h) - \bar{e}^{Pre}(i,t,t^e,h)\right]^2}, \tag{OA.4}$$

where $\bar{e}^{Pre}(i,t,t^e,h)$ is the median estimate across all analysts in $\mathcal{A}_{i,t,t^e,h}$ at the acceptance time of the earliest filing on t. That is, $RMSDMedPreCh_{i,t}$ measures how far analysts' estimates drifted from the median estimate because of the company disclosure.

The remaining dependent variables are also the difference between the average RMSDs post and pre-filing, but the deviations are instead taken from estimates 20 days after t at 4 PM. Specifically, $\bar{e}^{Pre}(i,t,t^e,h)$ in Equation (OA.4) is replaced with the analyst's own estimate $e^{t+20}(a,i,t,t^e,h)$ at the end of $t+20$ in the definition of *RMSDOwnFutCh* and with the median estimate $\bar{e}^{\,t+20}(i,t,t^e,h)$ at the end of $t+20$ in the definition of *RMSDMedFutCh*. These outcome variables indicate how much closer analyst forecasts from future more-informed estimates are as a result of the company's filings.

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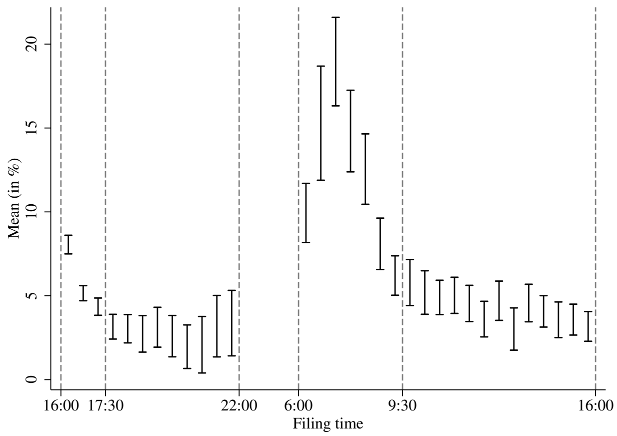
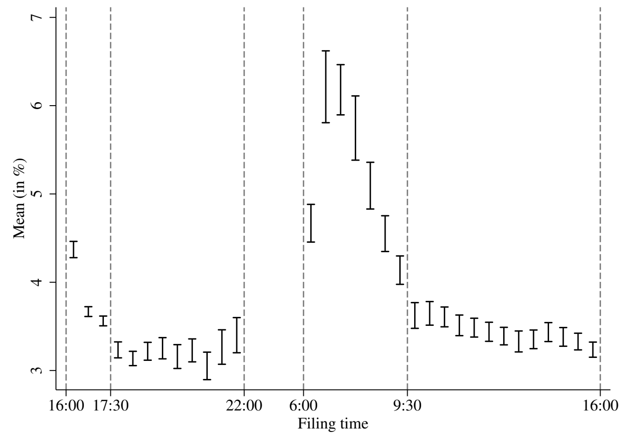
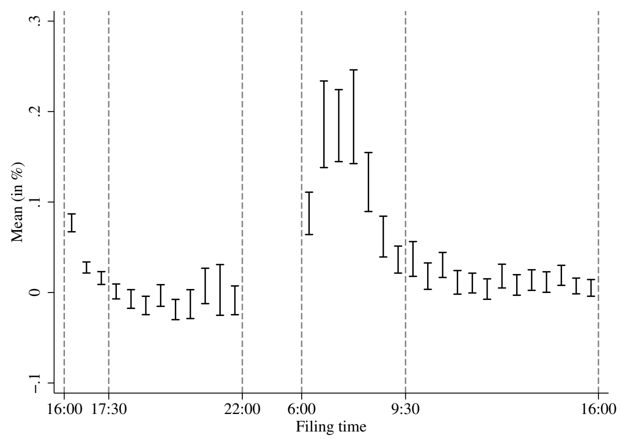


(a) Abnormal return as percentage of 31-day CAR



(b) Volume as percentage of 31-day cumulative volume



(c) Abnormal idiosyncratic volatility

Figure OA.1: Price informativeness across filing times. The figure displays the 95% confidence intervals for the mean values of three variables associated with price informativeness across the 30-minute time intervals the SEC accepts filing submissions. The estimates are from running a regression of the outcome variables on dummies for the filing time of the earliest SEC filing submitted on the report date, firm fixed effects, and trading day fixed effects. The dashed gray vertical lines divide the whole day into subperiods. After-hour filings received from 4 PM to 5:30 PM are immediately available on EDGAR, whereas those submitted from 5:30 PM to 10 PM are only accessible starting 6 AM the following trading day. Afterward, there is an 8-hour interval from 10 PM to 6 AM when the SEC does not accept any filings. Reports can again be filed starting at 6 AM, even before markets open at 9:30 AM. Standard errors used for the 95% confidence intervals are two-way clustered at the firm and trading day levels. The title of each panel is the dependent variable in the regressions. The variables are defined in Table 1 of the main text.

Table OA.1: Frequency of filing types. This table reports the number, together with the cumulative percentage, of SEC reports submitted from October 1, 2015, to March 8, 2017 per filing type. The list is ordered from the most frequent to the least.

Filing type	No.	Cum. %
4	82,164	54.83%
8-K	26,946	72.81%
SC 13G	6,363	77.06%
10-Q	6,017	81.07%
424B2	4,456	84.05%
3	2,984	86.04%
10-K	2,370	87.62%
424B3	2,018	88.97%
425	1,900	90.23%
DEFA14A	1,738	91.39%
SC 13D	1,599	92.46%
DEF 14A	1,391	93.39%
FWP	1,370	94.30%
5	1,352	95.21%
S-8	772	95.72%
424B5	751	96.22%
CORRESP	515	96.57%
S-3	410	96.84%
DFAN14A	327	97.06%
CT ORDER	293	97.25%
11-K	290	97.45%
UPLOAD	285	97.64%
SD	259	97.81%
S-4	246	97.97%
S-3ASR	205	98.11%
13F-HR	196	98.24%
S-8 POS	176	98.36%
PRE 14A	173	98.48%
SC TO-C	169	98.59%
SC TO-T	137	98.68%
EFFECT	116	98.76%
8-A12B	105	98.83%
SC TO-I	105	98.90%
SC14D9C	94	98.96%
IRANNOTICE	90	99.02%
D	85	99.08%
NT 10-Q	80	99.13%
SC 14D9	80	99.18%
POS AM	76	99.23%
144	71	99.28%
424B7	70	99.33%
NO ACT	68	99.37%
NT 10-K	67	99.42%
PREC14A	61	99.46%
DEFM14A	52	99.49%
PRER14A	51	99.53%
POSASR	45	99.56%
S-1	43	99.59%
PREM14A	36	99.61%
13F-NT	35	99.63%
CERTNYS	35	99.66%
DEFR14A	35	99.68%
DEFC14A	33	99.70%
PRRN14A	31	99.72%
PX14A6G	29	99.74%
ARS	25	99.76%
RW	23	99.77%
SC 13E3	23	99.79%
424B8	19	99.80%
25	17	99.81%
424B4	17	99.83%
25-NSE	15	99.84%
6-K	15	99.85%
DEF 14C	15	99.86%
15-15D	13	99.86%
40-17G	13	99.87%
ABS-15G	13	99.88%
305B2	11	99.89%
CERTNAS	11	99.90%
PRE 14C	9	99.90%
10-12B	8	99.91%
AW	8	99.91%
DEL AM	8	99.92%
POS 8C	8	99.92%
40-33	7	99.93%
8-A12G	7	99.93%
8-K12B	7	99.94%
N-2	7	99.94%
15-12B	6	99.95%
POS EX	6	99.95%
PREM14C	6	99.95%
10-KT	5	99.96%
497	5	99.96%
497AD	5	99.96%
S-3MEF	5	99.97%
T-3	5	99.97%
40-17F2	3	99.97%
40-APP	3	99.97%
APP ORDR	3	99.98%
PRER14C	3	99.98%
DEFM14C	2	99.98%
DEFN14A	2	99.98%
DFRN14A	2	99.98%
F-4	2	99.98%
NT 11-K	2	99.99%
PREN14A	2	99.99%
S-11	2	99.99%
10-12G	1	99.99%
10-QT	1	99.99%
15-12G	1	99.99%
40-F	1	99.99%
424B1	1	99.99%
APP NTC	1	99.99%
APP WD	1	99.99%
AW WD	1	99.99%
CB	1	99.99%
DEFR14C	1	99.99%
NTN 10K	1	100.00%
NTN 10Q	1	100.00%
S-1MEF	1	100.00%
S-3D	1	100.00%
S-3DPOS	1	100.00%
S-4 POS	1	100.00%
S-4MEF	1	100.00%
SC 14F1	1	100.00%

Table OA.2: Correlation among observables. This table reports the correlation matrix of a number of variables, defined in Table 1 of the main text.

	ErrorExp	IPs1	PctARPre	CAR	AbsCAR	PctInst	Analysts	I(Fri.)	MktCap	MTB
ErrorExp	1.000	−0.020	0.005	0.019	−0.028	−0.009	0.012	0.007	−0.010	0.017
IPs1		1.000	0.001	−0.005	0.003	0.012	0.099	0.043	0.118	0.012
PctARPre			1.000	0.018	−0.009	0.011	0.008	0.012	−0.005	−0.003
CAR				1.000	−0.050	−0.004	−0.007	−0.003	−0.004	−0.033
AbsCAR					1.000	−0.093	−0.126	−0.006	−0.141	0.002
PctInst						1.000	0.335	−0.006	0.009	0.041
Analysts							1.000	0.004	0.494	0.087
I(Friday)								1.000	0.003	0.003
MktCap									1.000	0.040
MTB										1.000

	MOM	I(Ins.)	I(Curr.)	I(Per.)	I(Proxy)	I(Earn.)	NFilings	Illiq	Vol	FileSize
ErrorExp	0.061	0.160	−0.144	0.039	−0.045	−0.055	0.037	−0.010	−0.092	0.021
IPs1	−0.013	−0.075	0.061	0.141	0.025	0.063	0.038	−0.017	−0.006	0.140
PctARPre	0.002	0.050	−0.066	0.005	−0.003	−0.085	0.017	0.002	−0.008	−0.004
CAR	−0.088	0.025	−0.019	0.021	0.018	0.017	0.002	0.012	−0.075	0.013
AbsCAR	−0.055	−0.050	0.045	0.024	0.001	0.020	−0.033	0.083	0.378	0.008
PctInst	−0.030	0.064	−0.033	−0.027	−0.015	−0.013	0.054	−0.360	−0.139	0.020
Analysts	−0.055	0.059	−0.065	−0.054	−0.022	−0.048	0.111	−0.225	−0.166	0.032
I(Friday)	−0.005	0.007	−0.068	−0.006	0.043	−0.121	0.002	0.005	0.018	−0.008
MktCap	0.027	0.010	−0.054	−0.043	−0.016	−0.034	0.140	−0.076	−0.252	0.021
MTB	0.151	0.051	−0.028	−0.008	−0.015	−0.007	−0.011	−0.051	0.011	−0.045
MOM	1.000	0.045	−0.024	−0.010	−0.034	−0.006	−0.008	−0.043	−0.195	−0.025
I(Insiders)		1.000	−0.532	−0.261	−0.138	−0.303	0.318	−0.050	−0.082	−0.257
I(Current)			1.000	0.011	−0.068	0.407	−0.126	0.026	0.043	0.059
I(Periodic)				1.000	−0.050	0.327	−0.039	0.034	0.009	0.629
I(Proxy)					1.000	−0.050	−0.004	0.012	0.048	0.027
I(Earnings)						1.000	−0.065	0.022	−0.016	0.200
NFilings							1.000	−0.042	−0.054	0.065
Illiq								1.000	0.163	−0.018
Vol									1.000	−0.019
FileSize										1.000

Table OA.3: Only non-consecutive firm-days. This table reports the estimates from panel regressions of three variables associated with price informativeness on the interaction between the logged number of IP addresses attempting to download a filing—*Log(IPs1)*—and a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections. For each firm, we drop a report day if there is at least one filing on the day before or after it. The controls are as in Table 2 of the main text. All variables are defined in Table 1. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		-0.534^{***}		-0.142^{***}		-0.007^{***}
		(-2.82)		(-7.80)		(-3.24)
Log(IPs1)	1.294^{***}	1.392^{***}	0.471^{***}	0.496^{***}	0.021^{***}	0.022^{***}
	(6.69)	(7.09)	(22.27)	(22.33)	(7.62)	(7.82)
ErrorExp		-0.422^{*}		-0.151^{***}		-0.005
		(-1.83)		(-6.47)		(-1.64)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,629	46,629	46,629	46,629	7,147	7,147
Adjusted R^2	0.121	0.121	0.315	0.316	0.508	0.509

Table OA.4: Other definitions of abnormal return. This table reports the estimates from panel regressions of the ratio *PctAR* between the filing-day abnormal return and the T+1-day cumulative abnormal return *CAR* around the filing date on the interaction between the logged number of IP addresses attempting to download a filing—*Log(IPs1)*—and a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections. In Panel A, T is 20, observations with absolute value *AbsCAR* of *CAR* at most 5% are dropped, and abnormal return is the alpha from either the Fama and French (1993) 3-factor (FF3) model, the Fama and French (2015) 5-factor (FF5) model, or the FF5 model with the momentum factor (MOM) of Carhart (1997). In Panel B, abnormal return is the CAPM alpha, observations with *AbsCAR* at most 5% are dropped, and T is either 5, 10, or 15. In Panel C, abnormal return is the CAPM alpha, T is 20, and observations with *AbsCAR* at most 1%, 2%, or 10% are dropped. The controls are as in Table 2 of the main text. All variables are defined in Table 1 of the main text. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Other factor models

Dependent variable:	FF3		FF5		FF5+MOM	
PctAR (in %)	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		−0.477***		−0.442**		−0.454**
		(−2.86)		(−2.52)		(−2.57)
Log(IPs1)	1.811***	1.895***	1.695***	1.772***	1.702***	1.781***
	(10.87)	(11.23)	(10.83)	(11.10)	(11.36)	(11.59)
ErrorExp		−0.403*		−0.423*		−0.448*
		(−1.85)		(−1.86)		(−1.88)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,940	66,940	66,615	66,615	66,370	66,370
Adjusted R^2	0.122	0.122	0.119	0.119	0.119	0.119

Panel B: Other evaluation windows

Dependent variable:	T = 5		T = 10		T = 15	
PctAR (in %)	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		−0.654***		−0.482***		−0.373**
		(−3.49)		(−3.33)		(−2.25)
Log(IPs1)	2.018***	2.130***	1.943***	2.033***	1.807***	1.872***
	(11.04)	(11.14)	(10.84)	(10.94)	(10.31)	(10.37)
ErrorExp		−0.699***		−0.315		−0.370*
		(−2.99)		(−1.61)		(−1.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

(Continued)

Table OA.4–*Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	55,451	55,451	60,658	60,658	64,826	64,826
Adjusted R^2	0.279	0.279	0.180	0.180	0.148	0.148

Panel C: Other cutoffs for absolute cumulative abnormal return

Dependent variable:	AbsCAR > 1%		AbsCAR > 2%		AbsCAR > 10%	
PctAR (in %)	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		-0.723^{***}		-0.539^{***}		-0.316^{**}
		(-2.98)		(-2.79)		(-2.24)
Log(IPs1)	1.346^{***}	1.477^{***}	1.434^{***}	1.529^{***}	1.707^{***}	1.760^{***}
	(5.86)	(6.32)	(7.54)	(7.87)	(10.53)	(10.58)
ErrorExp		-0.629^{**}		-0.545^{**}		-0.292
		(-2.11)		(-2.34)		(-1.61)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	106,463	106,463	96,169	96,169	37,380	37,380
Adjusted R^2	0.061	0.061	0.079	0.079	0.149	0.149

Table OA.5: Controlling for filing type. This table reports the estimates from panel regressions of three variables associated with price informativeness on the interactions of the logged number of IP addresses attempting to download a filing—*Log(IPs1)*—with a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections and filing type dummies. The controls are as in Table 2 of the main text. All variables are defined in Table 1 of the main text. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is from October 1, 2015, to March 8, 2017. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp	-0.306^{*}	-0.459^{***}	-0.069^{***}	-0.101^{***}	-0.006^{***}	-0.007^{***}
	(−1.86)	(−2.73)	(−4.62)	(−5.62)	(−3.92)	(−3.79)
Log(IPs1)	1.773^{***}		0.636^{***}		0.025^{***}	
	(10.31)		(30.06)		(12.10)	
ErrorExp	−0.327	-0.386^{*}	-0.113^{***}	-0.126^{***}	-0.006^{***}	-0.007^{***}
	(−1.61)	(−1.84)	(−5.27)	(−5.43)	(−3.30)	(−3.62)
Log(IPs1)×I(Insiders)	-0.471^{***}	-0.577^{***}	-0.189^{***}	-0.158^{***}	-0.004^{**}	-0.008^{***}
	(−3.10)	(−3.25)	(−10.66)	(−8.49)	(−2.14)	(−3.74)
Log(IPs1)×I(Current)	0.930^{***}	0.904^{***}	0.254^{***}	0.236^{***}	0.009^{***}	0.007^{***}
	(5.19)	(4.88)	(11.62)	(10.34)	(4.12)	(2.85)
Log(IPs1)×I(Periodic)	-0.444^{***}	-0.603^{***}	-0.071^{***}	-0.075^{***}	−0.003	-0.005^{**}
	(−2.87)	(−3.52)	(−3.76)	(−3.71)	(−1.62)	(−2.41)
Log(IPs1)×I(Proxy)	0.483^{***}	0.411^{***}	0.131^{***}	0.104^{***}	0.000	−0.002
	(3.33)	(2.91)	(5.65)	(4.60)	(0.03)	(−1.17)
Log(IPs1)×I(Earnings)	0.891^{***}	0.746^{***}	0.161^{***}	0.141^{***}	0.015^{***}	0.015^{***}
	(4.51)	(3.36)	(6.94)	(5.63)	(4.44)	(4.79)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
All FE × Log(IPs1)		Yes		Yes		Yes
Observations	68,349	68,349	68,349	68,349	11,832	11,832
Adjusted R^2	0.122	0.129	0.305	0.337	0.496	0.524

Table OA.6: Other event windows. This table reports the estimates from panel regressions of three variables associated with price informativeness on the interactions of the logged number of IP addresses attempting to download a filing—*Log(IPs1)*—with a proxy *ErrorExp* for the exposure of the IP addresses to unsuccessful redirections and filing type dummies. The controls are as in Table 2 of the main text. All variables are defined in Table 1 of the main text. Filing time fixed effects are dummies for the 30-minute time interval during which the earliest filing on the report date is electronically filed. The sample period is Q quarters before and after June 20, 2016. Q is 1, 2, and 4 in Panels A, B, and C, respectively. All regressors, except *ErrorExp*, are standardized. *ErrorExp* is set to have unit standard deviation after June 20, 2016. Standard errors are two-way clustered at the firm and filing date levels. The t-statistics are shown in parentheses. The symbols *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: One-quarter window

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		-0.548^{**}		-0.147^{***}		-0.012^{***}
		(-2.17)		(-5.45)		(-3.88)
Log(IPs1)	2.013^{***}	2.121^{***}	0.657^{***}	0.684^{***}	0.027^{***}	0.030^{***}
	(6.85)	(7.08)	(16.16)	(16.33)	(7.19)	(7.53)
ErrorExp		-0.410		-0.193^{***}		-0.009^{**}
		(-1.15)		(-5.11)		(-2.44)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,973	21,973	21,973	21,973	3,707	3,707
Adjusted R^2	0.150	0.150	0.285	0.286	0.518	0.519

Panel B: Two-quarter window

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		-0.612^{***}		-0.163^{***}		-0.009^{***}
		(-3.16)		(-8.24)		(-4.42)
Log(IPs1)	1.782^{***}	1.891^{***}	0.592^{***}	0.618^{***}	0.024^{***}	0.026^{***}
	(8.67)	(9.00)	(23.27)	(23.04)	(8.66)	(8.75)
ErrorExp		-0.436^{*}		-0.196^{***}		-0.010^{***}
		(-1.75)		(-7.18)		(-3.74)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45,881	45,881	45,881	45,881	8,059	8,059
Adjusted R^2	0.113	0.113	0.280	0.281	0.497	0.498

(Continued)

Table OA.6–*Continued*

Panel C: One-year window

	Dependent variable (in %)					
	PctAR		PctVolume		AbIdVol	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(IPs1)×ErrorExp		−0.466***		−0.140***		−0.008***
		(−3.77)		(−10.98)		(−6.00)
Log(IPs1)	1.525***	1.614***	0.563***	0.589***	0.021***	0.023***
	(11.08)	(11.44)	(30.25)	(30.20)	(10.23)	(10.49)
ErrorExp		−0.438***		−0.161***		−0.008***
		(−2.85)		(−9.06)		(−4.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm, date, and filing time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91,735	91,735	91,735	91,735	15,559	15,559
Adjusted R^2	0.119	0.119	0.290	0.291	0.488	0.489