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Is news really news? The effects of selective disclosure regulations

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Abstract

Before regulations were enacted to prevent such practices, information leaked through selective disclosure was incorporated into markets prior to the public release of news. "News days" did not deliver news to markets; now they do. We provide novel evidence of changes in returns and turnover behavior around the enactment of regulations barring selective disclosure practices in the United States and the EU. We conversely document lack of such changes in Australia and Japan, which did not implement similar measures. We conclude that selective disclosure resolves Roll's R^2 puzzle.

Keywords: news; media; information; price efficiency.
JEL classifications: G14, G15, G18

1. Introduction

In Richard Roll's (1988) presidential address to the American Finance Association,[1] he laments the failure of our profession to explain stock price changes even with hindsight. Noting that asset prices are determined by broad economic forces as well as firm-specific factors, he compares the returns of individual stocks during periods with and without media coverage. His intuition is that during periods without news, stocks should move closely with the market, leading to high regression R^2, or equivalently, low idiosyncratic volatility.[2] By contrast, the release of firm-specific news should be associated with price adjustments as the information is incorporated into the stock price, leading to a low R^2 and high idiosyncratic volatility. Using a sample of daily returns for individual US stocks and a simple definition of what counts as a "news day," Roll documents virtually no gap between the R^2 measures during news and non-news days. He concludes "these results are not very gratifying."

What could cause this result? An immediate implication is that "news" reports contained no real news to investors. One explanation is information leakage prior to public news release. This information then becomes incorporated into market prices by a limited and privileged pool of investors. When the information finally reaches the general public on the "news day," it has largely been incorporated into prices already. Indeed, a large literature

1 Summarized at Roll (1988).
2 Roll's R^2 is from a regression of observed returns on model-predicted returns, using the CAPM (Capital Asset Pricing Model) as the predictive model. R^2 then equals systematic variance divided by the sum of systematic and idiosyncratic variance. Thus, Roll's results could be equivalently restated in terms of idiosyncratic variance. For a given beta, there is a one-to-one relation between the two measures.

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in finance and accounting documents that selective disclosure prior to news release has been a pervasive issue. Potential motives for selective disclosure include agency cost explanations (currying favor with investors and investment banks); damage control scenarios (leaking bad news to sympathetic analysts in small doses to "soften the blow"); or nefariously leaking information to an inner circle to front-run public news.

In 2001, the SEC acted to address this pervasive issue with the passage of Regulation Fair Disclosure (Reg FD). Prior to the passage of Reg FD, firms were permitted to selectively disclose information to preferred analysts and investors before the rest of the public. This regulation was an attempt to level the playing field by requiring that all investors be given simultaneous access to the same information. The EU followed suit with a series of closely related regulations—the Market Abuse Directive (MAD) and Directive 2004/109 (Harmonization of Transparency Requirements)—which went into force in 2005. By contrast, Japan (JP) did not enact similar regulations until 2018, and Australia (AU) has never done so. To the extent that selective disclosure regulations (SDRs) were effective and information leakage from selective disclosure was to blame for Roll's puzzle, we should see a structural break occurring at these passage dates. Post-SDRs, market response to news coverage should act in the gratifying way that Roll expected (and theory predicts), but did not find.

We develop our hypotheses formally using a two-period model based on Kyle (1985). Date two is an announcement period in which firm value is revealed publicly. Date one allows for exogenous leakage of firm news to a single privileged trader. Noise trading occurs in both periods. Regulation is modeled as a reduction in the strength of the leaked signal. As in the Kyle model, a market maker (MM) sets prices in a semi-strong efficient manner, given the order flow. We characterize the behavior of stock returns in each period and analyze how the idiosyncratic volatility of these returns varies with the strength of the leaked signal.

In the absence of SDRs, information leakage is high and significant price discovery occurs at both $T=1$ and $T=2$. Idiosyncratic return volatility is moderately high in both periods. Return volatility occurs in the first period via selective disclosure (through the price impact of the informed trader (IT)), and in the second period due to residual information becoming public knowledge. By contrast, SDRs reduce price discovery at $T=1$, leaving more of it until $T=2$. This scenario leads to low idiosyncratic return volatility at $T=1$, and high volatility at $T=2$ when news hits. This pattern aligns with Roll's theoretical perspective.

We hence hypothesize that SDRs decrease idiosyncratic return volatility—or equivalently increase R^2—on non-news days compared to public news days. We examine this hypothesis using two related measures of what qualifies as public news. Following Roll, one measure is based on the number of times a firm is mentioned in media outlets on a given day; we describe in Section 3 how we detect spikes in this measure. Another large literature uses earnings announcement dates as a proxy for news. For additional robustness, and because these two measures are likely to suffer from different balance of Type 1 and Type 2 errors, we present our main results with both measures.[3]

We provide novel evidence that US market behavior changed considerably around 2001, aligned with the passage of Reg FD, in ways predicted by the model. EU market behavior saw similar changes around 2005, aligned with the passage of MAD.[4] We further show

[3] EADs potentially represent a very clean test in terms of Type 1 errors; earnings announcements are undeniably value relevant. On the other hand, EADs suffer from Type 2 errors (omitting days with value-relevant events). EADs occur just 4 days a year and thus miss many important events: CEO turnover, mergers, FDA trial outcomes, product launches, credit rating downgrades, etc. All such events are covered by the media.

[4] We pinpoint the timing of structural changes in market behavior using the regime-switching regression method of Hamilton (1989). This method estimates both the date and frequency of regime switches from the data and has been previously used to research the impact of regulation changes on economic outcomes by, for example, Hamilton (1988), Sims and Zha (2006), and Davig (2004).

that no such changes happened in AU or JP. Importantly, these highly staggered regulation enactment dates (2001, 2005, 2018, never) allow us to rule out explanations driven by an omitted time-dependent factor affecting all developed markets simultaneously. Such ruled-out explanations include (1) the dot-com crash; (2) the migration of news from print to on-line; and (3) the rise of passive index investing. These and other global phenomena occurred contemporaneously in the United States, EU, JP, and AU.

The changes in market behavior are economically large and statistically robust. For our primary diff-in-diff tests, we compute the difference between return R^2 on non-news days and news days ("R^2 dip"), and examine whether it increases following the passage of SDRs. For example, using earnings announcement days (EADs) as the news event, we show that the return R^2 dip on news days has grown by a factor of more than 5, from a mean of just 0.04 to a mean of 0.20 pre- and post-2001. These changes are statistically significant at the 0.1 percent level and are robust under a variety of formulations. We find broadly similar results in the EU (with slightly reduced magnitudes) and coefficients generally near zero for AU and JP. We also construct a placebo test using FOMC and PPI/CPI announcement days as our news event. SDRs affect firm-specific news rather than market-wide information, and thus we expect this placebo test to yield null results. We document that the relevant coefficients in all such specifications are, without exception, very close to zero.

In addition to returns, the existing literature also examines trading volume or turnover as a measure of information revelation.[5] Although our model does not directly generate hypotheses for trade sizes,[6] for completeness, we examine this issue empirically. We create turnover analogs for all of our return volatility measures and repeat the analysis, finding broadly similar results.

2. Background, model, and hypothesis development

Our article intersects with three literature domains: (1) the impact of news media on financial markets, (2) the influence of securities regulations, and (3) factors determining return R^2. We review these areas before presenting the model and formulating our hypotheses.

2.1 Media and financial market behavior

Media coverage affects financial markets. Fang and Peress (2009) find that stocks not covered by the media earn higher returns. Patton and Verardo (2012) study propagation of news across firms. Tetlock (2007) shows that pessimistic tone in media coverage predicts low returns, but these returns are subsequently reversed. Barber and Odean (2008) show that individual investors are net buyers of "attention grabbing" stocks. Tetlock (2011) shows that investors overreact to "stale" news defined by textual similarity to previously published articles. Engelberg and Parsons (2011) and Peress (2014) use media strikes to show causal effects of media. Kaniel and Parham (2017) use regression discontinuity to directly show the causal impact of media mentions on investor behavior in the context of mutual fund flows.

Engelberg, Reed, and Ringgenberg (2012) find that the negative relation between short sales and future returns is twice as large on news days. Engelberg, Mclean, and Pontiff (2018) show that return anomalies tend to be concentrated on news days. Both results are consistent with investors having uncertain beliefs which are resolved when news is publicly released. These samples span both pre-Reg FD and post-Reg FD eras. Finally, Tetlock (2010) examines a dataset of 2.2 million articles between 1979 and 2007 to characterize

5 See, for example, Bailey et al. (2003).

6 In our Kyle model with risk-neutral players, we show that selective disclosure tip-off quality affects the expected profits of the informed trader, but not his mean trade size. This is an artifact of risk-neutrality: a risk-averse trader would likely temper his trades in response to noisier information.

the connection between news publication and contemporaneous and future returns. He finds that news days are associated with less future reversals, higher correlation between volatility and turnover, and reduced price impact of order flow.

None of the aforementioned papers share our focus: the differential impact of SDR passage on return (and turnover) predictability on news days vs. non-news days.

2.2 SDRs

The impact of Reg FD has been cataloged in a considerable literature in accounting and finance. Reg FD is associated with a decline in the number of analysts per firm, a decline in the accuracy of analyst forecasts, and an increase in the frequency of earnings guidance.[7] This evidence is consistent with a substitution away from selective disclosure toward public disclosure, as Reg FD intended. Heflin, Subramanyam, and Zhang (2003) find that firms react to RegFD by increasing the frequency of voluntarily disclosures, and they find lower return volatility on EADs which they interpret as improved informational quality. Bailey et al. (2003) and Francis, Nanda, and Wang (2006) by contrast both find no change in return volatility, although Bailey et al. (2003) find heightened trading volume which they interpret as heightened disagreement, and Francis, Nanda, and Wang (2006) find that analysts forecasts become less accurate, consistent with a reduction of information flow to analysts. Koch, Lefanowicz, and Robinson (2013) survey the related literature and conclude that indeed Reg FD has the intended effect of reducing selective disclosure.

Unlike our article and Roll's (1988), none of these papers examine media coverage. Similarly, none compare return behavior on news days and non-news days. Notably, the SEC allows an exception for selective disclosure to media[8] so that firm insiders may speak freely to the press in private, just as they were able to before Reg FD. This is likely to preserve the information content of media after Reg FD passage.

Following Reg FD, the European Union (EU) promulgated a series of SDRs with similar goals as Reg FD. In April 2003, EU regulators passed the MAD which is similar to Reg FD but broader in scope. MAD not only forbids selective disclosure but also mandates continuous disclosure (i.e., firms cannot withhold material information but must instead disclose it "as soon as possible"). However, MAD lacks implementation details, instead leaving interpretation and enforcement to individual member states. Payne (2019) shows member states had historically failed to apply securities regulations in a uniform fashion. MAD is revised and extended by Directive 2004/109 ("Harmonisation of Transparency Requirements") which passed on December 2004 and went into force on October 2005. This directive reiterates the goal of a level playing field for all investors—the same language as in Reg FD—while formalizing and unifying the rules across the EU regarding exactly how firms must disseminate information via an officially recognized news service.

Unlike the United States and EU, JP and AU failed to deploy SDRs in a timely manner. As late as 2015, Goetzmann and Hamao (2015) document rampant selective disclosure in JP. The Japanese Financial Services Agency proposed a selective disclosure amendment on December 2016, Japan's Upper House of Parliament (the Diet) passed it as Act No. 49 on May 2017, and it was promulgated on April 2018. Contrary to the previous locales, AU has never enacted a selective disclosure rule. North (2009) states "There is no specific selective disclosure regulation in AU," and this observation has not changed in recent years.

2.3 Determinants and interpretation of return R^2

Morck, Yeung, and Yu (2000) show that average return R^2 is higher in developing countries and in those with poor governance. Campbell et al. (2001) find a declining trend of

[7] See: Mohanram and Sunder (2006); Agrawal, Chadha, and Chen (2006); Wang (2007); Sun (2009); Srinidhi, Leung, and Jaggi (2009).

[8] See Section 1a of https://www.federalregister.gov/documents/2000/08/24/00-21156/selective-disclosure-and-insider-trading.

return R^2 in the United States between 1960 and 1997. Jin and Myers (2006) show that average return R^2 declined across the world during the 1990s. Durnev et al. (2003) show that firms with low return R^2 have a higher association between current returns and future earnings changes. Together, these results paint a picture that low return R^2 indicates more informative stock prices. Other evidence suggests a contrary view.

Whereas this branch of research studies average return R^2, they do not examine media coverage or the release of news. In contrast, our results relate closely to Boudoukh et al. (2019) and Griffin, Hirschey, and Kelly (2011), both of which also overturn an aspect of Roll (1988) but do so in different ways. Boudoukh et al. (2019) use textual analysis to read and classify news based on supervised learning. Their algorithm flags articles expected to be value relevant (they call this sub-sample "identified" news). Return R^2 is only 17.7 percent on days with this identified value-relevant news, as compared to 34.5 percent on other days. They conclude that a small subset of media coverage acts as bona-fide news as predicted by Roll and that this subset is ex-ante identifiable. Griffin et al. (2011) examine the international differences in the return R^2 gap between news and non-news days. They document that the difference is consistently larger in developed countries.

We follow both papers in concentrating on the R^2 gap between news and non-news days. The Boudoukh et al. (2019) sample covers 2000–2015, whereas Griffin et al. (2011) cover 2003–2009. Both studies therefore examine eras which are almost entirely post-Reg FD (and/or post-MAD). As such, neither consider the impact of SDRs on their results.

2.4 A simple model of informed trade

We model selective disclosure using a two-period model based on Kyle (1985). News about an asset's value is disclosed publicly at a predetermined time $t=2$ (the "news day"). An IT receives a "tipoff" from an analyst at $t=1$ (the "non-news day") allowing it to front-run this public disclosure. We model SDRs as varying the strength of the tipoff signal received at $t=1$.[9] The strength of this signal is a key variable in our model, ranging continuously from a scenario where the tipoff fully reveals all information (representing a complete lack of SDRs or other frictions) to a scenario where no information is disclosed (representing fully enforced SDRs). We analyze trading at both $t=1$ and $t=2$, focusing on the mean and variance of stock returns, turnover, and the IT's profits. We investigate how these metrics respond to variations in the intensity of SDR enforcement.

As in the Kyle model, the three risk-neutral traders are the IT, uninformed trader (UT), and MM. The traders trade a single risky asset with ex-post liquidation value $v \sim \mathbb{N}(\mu_v, \sigma_v^2)$, which is revealed publicly at $t=2$. The MM sets the prices p_t efficiently (in the semi-strong sense) conditional on its information set, which includes the combined order flow of the IT and UT at period t, y_t. Thus, the MM earns zero profit in expectation. The UT's order flows are stochastic and given by $u_t \sim \mathbb{N}(0, \sigma_u^2)$. The IT maximizes expected profit and we denote its requested quantity at period t by x_t and the combined flow the MM observes is then $y_t = x_t + u_t$.

In a deviation from the Kyle model, we assume that at $t=1$ the IT receives a *noisy* private signal regarding the liquidation value of the asset, $\tilde{v} = v + s$ with $s \sim \mathbb{N}(0, \sigma_s^2)$.[10] We denote the correlation between the ex-post value v and the noisy signal $\tilde{v}$ as

$$\rho = \sqrt{\frac{\sigma_v^2}{(\sigma_v^2 + \sigma_s^2)}} \tag{1}$$

[9] Similar to Odean (1998), our model extends Kyle (1985) by considering an insider with noisy information. While Odean introduces overconfidence into the insider's decision-making, our model diverges by incorporating a second round of trading, allowing us to analyze stock price adjustments in response to public information received after selective disclosure.

[10] All traders know the model parameters $\mu_v, \sigma_v, \sigma_s, \sigma_u$, and the RVs v, s, u_0, u_1, u_2 are independent.

The correlation $\rho \in [0, 1]$ quantifies the quality of the signal $\tilde{v}$ in a parsimonious way. If the IT's signal is precise ($\sigma_s \to 0, \rho \to 1$), then we are back to the default Kyle setup. But as the IT's signal precision deteriorates ($\sigma_s \to \infty, \rho \to 0$), it loses its privileged position and becomes uninformed. This adjustment to the Kyle model allows us to quantify the *degree* of informativeness of the IT, rather than assuming it has full information of the ex-post liquidation value v as in Kyle (1985). In turn, it allows us to analyze the impact of SDRs without assuming that (1) prior to the passage of SDRs, the IT has *perfect* knowledge of the liquidation value; or that (2) after the passage of SDRs, the IT has *no* knowledge of the liquidation value.

Price determination and order flow during periods $t = 0$, 2 are hence degenerate. At $t = 0$, the IT lacks privileged knowledge and hence sets $x_0 = 0$. The MM receives order flow $y_0 = u_0$ from the UT and sets $p_0 = \mu_v$. At $t = 2$, the MM receives public information and sets the price $p_2 = v$ regardless of order flow. The IT's trade size is indeterminate at $t = 2$ owing to risk neutrality.[11]

The mathematical details are in Appendix A, but the solution takes a similar form as in the standard Kyle model. Specifically, the insider's demand is a linear function of his signal, and the MM's pricing function is a linear function of realized order flow. We show that these policies and the IT's expected profit are

$$\begin{aligned} p_1 &= \mu_v + \frac{\rho \cdot \sigma_v}{2 \cdot \sigma_u} \cdot y_1 \\ x_1 &= z_{\hat{v}} \cdot \sigma_u \\ \mathbb{E}[\pi] &= \frac{z_{\hat{v}}^2 \cdot \rho \cdot \sigma_v \cdot \sigma_u}{2} \end{aligned} \tag{2}$$

where $z_{\hat{v}}$ is a Z-transformation of $\hat{v}$ derived in the appendix. Defining the returns for periods 1, 2 to be $r_t = (p_t - p_{t-1})/p_{t-1}$, we have that

$$\begin{aligned} \frac{\partial x_1}{\partial \rho} &= 0 \\ \frac{\partial \mathbb{E}[\pi]}{\partial \rho} &> 0 \\ \frac{\partial \mathbb{V}[r_1]}{\partial \rho} &> 0 \\ \frac{\partial \mathbb{V}[r_2]}{\partial \rho} &< 0 \end{aligned} \tag{3}$$

or that a *lower* quality signal: (1) does not change the amount requested by the IT (a result stemming from risk-neutrality); (2) *decreases* the IT's expected profit; and (3) *decreases* return volatility in period 1 but *increases* it in period 2. With a lower quality signal, less information is embedded into the price during period 1, leaving more information as "surprise" for period 2. Put differently, the total amount of information to be revealed remains constant, but SDRs shift price discovery from non-news days to news days.

Appendix A extends the model to scenarios in which the IT can produce additional costly information, beyond the noisy information given by the selective disclosure tip.

[11] In a general model with risk-aversion and additional rounds of trading, the IT would unwind his position at $t = 2$ in order to limit exposure to future uncertainty.

For instance, a trader who receives highly precise information from a tip might decide to buy only a minimal amount of additional information. Conversely, a trader who receives a vague tip might opt to invest significantly in acquiring more information. However, our analysis demonstrates that decreasing selective disclosures results in a net decrease in the overall information available in the market. Although traders may try to offset the loss of the tip-off information by buying more, their efforts do not fully compensate, leading to a lower total information availability prior to public information release. Consequently, the same hypotheses as above hold in unchanged form for this expanded model.

2.5 Hypothesis development

We conclude with the following hypotheses:

> Hypothesis 1: *SDRs increase the "gap" between stock return volatility on news days relative to non-news days.*

The passage of SDRs is modeled as a decrease in ρ. From equation (3), return volatility on non-news days decreases and return volatility on news days increases. To partial out any time trends in either, the hypothesis is stated in terms of differences between news days and non-news days. Hence, the difference ("gap") between return volatility on news days and non-news days should increase. Because the model lacks a notion of a "market portfolio," we focus in testing the model on idiosyncratic volatility rather than total volatility, under the assumption that selective disclosure tipoffs concern firm-specific information rather than providing a preview of overall market conditions and movement.

In Section 3.3, we discuss the inverse relation between idiosyncratic volatility and return R^2. An increase in idiosyncratic volatility, holding systematic volatility constant, will imply a decrease in return R^2 of an asset pricing model. We hence equivalently write:

> Hypothesis 2: *SDRs increase the "gap" between return R^2 on non-news days relative to news days.*

According to equation (3), turnover is unchanged following the passage of SDRs. This irrelevance result is an artifact of risk-neutrality. In a more general model including risk-aversion of the insider, trade sizes of the IT would be moderated in cases where the signal is weaker. Such a model is beyond the scope of this article, but would seemingly generate analogous predictions for abnormal turnover and turnover R^2 as our Hypotheses 1 and 2.

Specifically, and all else equal, higher quality tipoffs would drive the IT to trade more aggressively on non-news days, which then lead to more aggressive unwinding on news-days. This imbalanced buildup of a position before news days (and rebalancing after news is revealed) should heighten abnormal trade volatility on non-news days relative to news days. This usage follows the literature reviewed in Sections 2.1 and 2.3, which uses volume (and turnover) differences similarly. We therefore conclude:

> Hypothesis 3: *SDRs increase the "gap" between turnover volatility on news days relative to non-news days.*

> Hypothesis 4: *SDRs increase the "gap" between turnover R^2 on non-news days relative to news days.*

3. Data and empirical methods

We test our hypotheses using data for the United States, EU, JP, and AU. As discussed above, the United States enacted an SDR (RegFD) in 1Q2001 and the EU enacted an SDR

(MAD) in 4Q2005. JP only enacted SDRs on 3Q2018, just at the end of our sample period, while AU did not enact SDRs during the sample period. We hence use JP and AU as placebo settings. We next present the data used and define our outcome variables and measures of interest.

3.1 Data and outcome variables

We collect the following data:

- S&P 500 return, volume, and turnover: daily, 7.1 million firm-days for 1, 289 firms in the S&P500 over 1980–2018—from CRSP.
- STOXX return, volume, and turnover data: daily, 9.3 million firm-days for 759, 961, and 2017 firms in the STOXX Europe 600, STOXX Japan 600, and STOXX Australia 150 indices respectively, over 1993–2018—from Bloomberg.
- EADs: 179K quarterly announcement and 60K annual announcement dates—from I/B/E/S.
- Factiva articles: 3.8 M, 6.0 M, 1.9 M, and 0.6 M article dates and headings for the United States, EU, JP, and AU samples, respectively—from Factiva.
- PPI, CPI, and FOMC meeting days: 763 "macroeconomic" dates over 1980–2018 for the United States—from FRED.
- Fama-French 3-factor returns: daily, for United States, Europe, Asia Pacific ex Japan, and JP—from Ken French's website.

As most outcomes of interest are in terms of expectational error—the difference between the observed and expected outcome—we begin by defining daily return, volume, turnover, and news interest, as well as their pre-expectations.

We define the (dividend- and split-adjusted, log-point, close-to-close) return of firm i during trading-day t as

$$r_{i,t} = \log(\text{price}_{i,t} + \text{div}_{i,t}) - \log(\text{price}_{i,t-1}) = \log(1 + \%\text{adjusted return}) \tag{4}$$

With price the split-adjusted closing price and div the dividend amount. We then define expected return as the value predicted by a Fama-French 3-factor model. We calculate the betas of stock i during month m by conducting rolling regressions of stock i's daily excess returns during the 12 months preceding month m (excluding month m) on the FF factor returns. The resulting expected return for firm i during trading-day $t \in m$ is denoted as $\mathbb{E}[r_{i,t}]$.

We define the firm's (log) trading volume as

$$v_{i,t} = \log(1 + \text{volume}_{i,t}) \tag{5}$$

where volume is measured in thousands of shares. We then define expected volume as the average of $v_{i,t}$ during the 12 preceding months. The resulting expected volume is denoted $\mathbb{E}[v_{i,t}]$. This is roughly following the method in, e.g., Heflin, Subramanyam, and Zhang (2003); Bailey et al. (2003); and Francis, Nanda, and Wang (2006), though we use the log transform to limit the impact of outliers and scale the data better, as in Campbell, Grossman, and Wang (1993).

We also consider turnover, following Campbell, Grossman, and Wang (1993) who find turnover to be a better-normalized measure than volume. We define the firm's (log) turnover as

$$u_{i,t} = \log\left(\frac{1 + \text{volume}_{i,t}}{\text{csho}_{i,t}}\right) = v_{i,t} - \log(\text{csho}_{i,t}) \tag{6}$$

where csho is the current shares outstanding, measured in thousands. We then define expected turnover in two ways. First, similar to expected volume, as the average of $u_{i,t}$ during the 12 preceding months. The resulting expected turnover is denoted $\mathbb{E}^{mean}[u_{i,t}]$. Second, for each firm we conduct rolling ARMA(1,1) regressions of $u_{i,t}$ during the preceding 12 months, with two lags of returns and absolute returns as controls, and day-of-the-week fixed effects. We use the model to predict expected turnover, denoting it $\mathbb{E}^{arma}[u_{i,t}]$. For each firm i and month m we estimate the model

$$u_{i,t} = \mu_{i,m} + \boldsymbol{\beta}_{i,m} \cdot \boldsymbol{Z}_{i,t} + \phi_{i,m} \cdot u_{i,t-1} + \varepsilon_{i,t} + \theta_{i,m} \cdot \varepsilon_{i,t-1} \tag{7}$$

using all trading days t during the 12 months preceding m, with $\boldsymbol{Z}_{i,t}$ the vector of controls above. We use the estimates to predict turnover during the trading days of month m. The prediction error of the ARMA(1,1) method is, perhaps unsurprisingly, considerably lower than that of the mean method, though it is more computationally taxing.[12] These results are in line with the recent findings of Bekaert, Bergbrant, and Kassa (2022), who test ten different methods for idiosyncratic volatility prediction and find ARMA(1,1) to be superior in terms of prediction error. We hence adopt $\mathbb{E}[u_{i,t}] = \mathbb{E}^{arma}[u_{i,t}]$ as our default definition of expected turnover.

Finally, we define the firm's (log) news interest as

$$s_{i,t} = \log(1 + \text{news}_{i,t}) \tag{8}$$

With news the number of (unique) news articles pertaining to the firm in Factiva's "News and Business Publications" category on day t. If a news article was published after 4 pm (local time) or over the weekend, we consider it to have been published during the next trading day (due to our return definition of close-to-close). We define $\mathbb{E}[s_{i,t}]$ in a manner analogous to expected turnover with ARMA(1,1) prediction, though without controlling for lagged returns to avoid conflating market data and news data, with good prediction accuracy as well.[13]

3.2 Identifying news days

We define a news day as a trading day during which new information is publicly released to the market. Our analysis includes two variations of this measure. First, in our main specification we follow the prior literature in using quarterly and annual EADs. Second, following Roll (1988), we construct a measure based on media citations (described in more detail below). These two measures complement each other, as they likely suffer from a different balance of Type 1 and Type 2 errors.[14]

To measure citations in the media, we obtain news articles from Factiva. Roll (1988) employs a binary measure, set to one if the firm was mentioned in the news on that day, and zero otherwise. This definition is inappropriate in the modern era, given the increased density of news (especially for large firms). Consequently, we characterize "spikes" in media coverage. For example, if a firm usually has no news pertaining to it, then a single news article may constitute a spike. For a more active firm, it may take 100 articles to constitute a spike. Goin and Ahern (2018) test several methods for the identification of spikes in economic time series. They too conclude that predicting the time series using a rolling ARMA (1,1) model and then considering the expectational error perform well in identifying spikes in the data. They further find that a threshold twice the size of the ARMA process's

12 Specifically, the R^2 values of regressing $u_{i,t}$ on $\mathbb{E}^{mean}[u_{i,t}]$ and on $\mathbb{E}^{arma}[u_{i,t}]$ are 0.67 and 0.79, respectively.

13 The R^2 values of regressing $s_{i,t}$ on $\mathbb{E}^{mean}[s_{i,t}]$ and on $\mathbb{E}^{arma}[s_{i,t}]$ are 0.48 and 0.58, respectively.

14 EADs potentially represent a very clean test in terms of Type 1 errors; earnings announcements are undeniably value relevant. On the other hand, EADs suffer badly from Type 2 errors (omitting days with value-relevant events). EADs occur just 4 days a year and thus miss many important events: CEO turnover, M&A, FDA trial outcomes, product launches, credit rating downgrades, etc. All such events are covered by the media.

standard deviation minimizes combined Type 1 and Type 2 errors. We follow them in defining a "news day" by setting $w_{i,t} = 0$ if $s_{i,t} - \mathbb{E}[s_{i,t}] \geq 2 \cdot \sigma_{i,m}$ with $\sigma_{i,m}$ the standard deviation of the ARMA model errors. The rolling ARMA approach is well suited to identifying news days in both sparse news environments (most days have no articles) and dense news environments (a significant number of daily articles regarding the firm). Furthermore, the method adjusts to trends and does not introduce a look-ahead bias.[15]

For both definitions of news (EADs and media citations), we employ the following conventions. The announcement day is day 0 of the event windows, denoted by $w_{i,t} = 0$, and the previous and following three trading days $\hat{t} \in \{t-3, \ldots, t-1, t+1, \ldots, t+3\}$ are denoted by $w_{i,\hat{t}} = \pm 3$ to ±1 accordingly. When using the Factiva measure, news days can in principle occur in quick succession. For example, a given day t might be both event day –2 and event day + 3 for two different news days of the same firm. For our analysis, we assign it to the closer day (e.g., in this example, it will be treated as day –2).

3.3 Defining outcome measures

After defining the core financial variables, their expectations, and what constitutes a news day, we are ready to define our event study setup and our main outcome measures. Prior to choosing outcome measures, it is useful to note that nearly all outcome measures used in the relevant literature cited above can be cast in terms of different aggregators for the expectational errors. For each locale l, within each quarter q, for each event-day $w \in [-3, 3]$, and for each of the financial variables $x \in \{r, v, u\}$ (return, volume, turnover), we define the following measures of expectational error during the quarter,

$$\begin{aligned}
\varepsilon_{x,i,t} &= x_{i,t} - \mathbb{E}[x_{i,t}] \\
\Xi^{avg}_{l,q,w,x} &= \mathrm{MEAN}[\varepsilon_{x,i,t}] \\
\Xi^{std}_{l,q,w,x} &= \mathrm{STD}[\varepsilon_{x,i,t}] \\
\Xi^{mad}_{l,q,w,x} &= \mathrm{MEAN}[|\varepsilon_{x,i,t}|] \\
\Xi^{Rsq}_{l,q,w,x} &= \mathrm{R}^2[x_{i,t}, \mathbb{E}[x_{i,t}]] = 1 - \left(\frac{\mathrm{STD}[\varepsilon_{x,i,t}]}{\mathrm{STD}[x_{i,t}]}\right)^2 \\
\Xi^{rho}_{l,q,w,x} &= \frac{\mathrm{STD}[\varepsilon_{x,i,t}]}{\mathrm{STD}[x_{i,t}]}
\end{aligned} \tag{9}$$

over all $x_{i,t}$ such that $w_{i,t} = w$ and $t \in q$. For example, $\Xi^{std}_{US,2005q1,0,r}$ denotes the idiosyncratic return volatility, in s.d. terms, of firms on news-days 0 during the first quarter of 2005 in the United States.

Note the first measure (*avg*) is a signed *location* measure and hence useful only when we have a prediction on the direction (i.e., sign) of expectational error. This is the case for both volume and turnover, for which both theory and prior empirical evidence predict an increase upon public news release. But it is not the case for return, for which the expectational error should be zero-mean. All other measures are merely different ways of measuring and normalizing the *dispersion* of expectational errors. The second measure (*std*) is the usual standard deviation measure of dispersion, which is more sensitive at detecting

[15] While Goin and Ahern (2018) find that a Kalman-filter-based method slightly outperforms the rolling ARMA method for spike detection, they show there are only minor differences between the two methods. Hence, we report results using the simpler rolling ARMA method. Repeating the analysis using a Kalman filter yields nearly identical results.

"outliers" (i.e., big return swings), while the third measure (*mad*) is less sensitive to outliers. More importantly, the *mad* measure is notable for conflating location and dispersion (or deriving identification from both), as it is sensitive both to location and to dispersion changes. This conflation may have made this measure a popular one for testing volume surprises in the literature.

The fourth measure (Rsq) is the R^2 measure used by Roll. It is easy to see that the *Rsq* measure is merely a function of the fifth measure (*rho*), itself just the expectational error volatility *std* normalized by the total volatility of $x_{i,t}$. That is, it is the share of idiosyncratic volatility out of the total. The *rho* measure can also be interpreted as measuring the correlation between $x_{i,t}$ and $\varepsilon_{i,t}$, such that $\Xi^{rho}_{l,q,w,x} = \text{CORR}[x_{i,t}, \varepsilon_{i,t}]$, which is the correlation between total and idiosyncratic return, after systematic return was factored out. The *Rsq* measure can similarly be interpreted as the squared correlation between $x_{i,t}$ and $\mathbb{E}[x_{i,t}]$. Both the *Rsq* and *rho* measures are normalized, unitless measures with intuitive meaning and which are limited to the $[0, 1]$ range, adding to their allure as clean dispersion measures, unaffected by units-of-measurement and robust to changes in systematic volatility.

Finally, note that the *level* of each outcome measure, as well as its trend over time, is largely outside our event-study, diff-in-diff empirical design (DiD). Our interest is in the *difference* in the levels, between news and non-news days of the same quarter, as well as that difference's time trend (the difference in this difference before and after the passage of SDRs). We define the first difference as

$$\Xi_{l,q,x} = \Xi_{l,q,(0),x} - \Xi_{l,q,(-3,-2,2,3),x} \tag{10}$$

The notation, for example, $\Xi_{l,q,(-3,-2,2,3),x}$ implies the value of Ξ for data x that were averaged over the window containing event days (−3, −2,2,3) in each event that took place during quarter q. We ignore days $(-1, 1)$ to avoid potential contamination, depending on variation on the exact timing of the event, news release, and market close/open. Although French and Roll (1986) find that the vast majority of volatility is realized during exchange trading hours, Bogousslavsky (2021) finds that price discovery using open-to-open is quite sensitive to small changes in open timing. This sensitivity favors our usage of close-to-close return measurement rather than open-to-open.[16] Our second difference will be between the values of $\Xi_{l,q,x}$ when $q < \tilde{q}_l$ and $q \geq \tilde{q}_l$, with $\tilde{q}_l$ the quarter at which SDRs were passed in the respective locale (and placebo dates for AU and JP). We describe these DiD test results next.

4. Results

4.1 Formal difference-in-difference tests

The basic pooled DiD setup can be described by

$$\Xi_{l,q,w,x} = \beta_{0,l,x} \cdot T_w \cdot A_q + \beta_{1,l,x} \cdot T_w + \beta_{2,l,x} \cdot A_q + \beta_{3,l,x} + \varepsilon_{l,q,w,x} \tag{11}$$

with $T_w = 1$ for news days $(w_{i,t} = 0)$ and 0 otherwise $(w_{i,t} \in \{-3, -2, 2, 3\})$, and $A_q = 1$ for $q \geq \tilde{q}_l$ and 0 otherwise. The basic pooled DiD specification is equivalent to a t-test for c

[16] To validate our timing assumptions defining day 0, and the decision to ignore days $(-1, 1)$, Appendix Table A1 presents the cross correlations between the expectational error measures by news day. It shows these correlations are similar and low on days (−3, −2,2,3), higher in days (−1,1), and very high on day 0. Appendix Table A2 presents the shifted correlations, that is, day 0 of one measure versus days (−1,0,1) of the other, yielding similar spikes. This indicates day 0 is well defined and that there is indeed some "spillage" to both days −1 and +1.

Table 1. SDRs and news day reactions—United States.

This table presents results of TWFE difference-in-difference tests, given by equation (12), in which $T_w \cdot A_q$ is the interaction term of news days ($T_w = 1$) and post-SDR ($A_q = 1$). In Panel (a), news days are defined as EADs, whereas in Panel (b) news days are defined based on Factiva news spikes. We report results over our three outcome variables: $x \in \{r, v, u\}$ (return, volume, turnover) using the five aggregation measures of equation (9). With $\varepsilon_{x,i,t} = x_{i,t} - \mathbb{E}[x_{i,t}]$ being the prediction errors (p.e.) for a given outcome variable x, firm i, and day t of a given quarter q, the quarterly aggregate measures are: (1) avg—mean p.e. during the quarter; (2) std—std. dev. of p.e.; (3) mad—mean absolute deviations of p.e.; (4) Rsq—the R^2 of the prediction; and (5) rho—the correlation between the observed and predicted values during the quarter. Reported t-values are based on HAC-robust standard errors. Asterisks denote significance at the 5 percent (*), 1 percent (**), and 0.1 percent (***) thresholds.

Panel (a)—EADs		avg	std	mad	Rsq	rho
ret:	$T_w \cdot A_q$	−0.001	0.029***	0.021***	−0.162***	0.093***
	$\hookrightarrow \lvert t \rvert$	1.19	10.20	12.20	6.38	5.88
	Within R^2	0.018	0.667	0.755	0.268	0.254
vol:	$T_w \cdot A_q$	0.412***	0.088***	0.374***	−0.049***	0.066***
	$\hookrightarrow \lvert t \rvert$	13.47	5.57	14.59	6.02	7.25
	Within R^2	0.689	0.276	0.780	0.330	0.390
trn:	$T_w \cdot A_q$	0.396***	0.102***	0.326***	−0.074***	0.076***
	$\hookrightarrow \lvert t \rvert$	12.14	6.97	15.03	6.88	8.17
	Within R^2	0.672	0.381	0.815	0.304	0.364
Panel (b) - Factiva spikes		**avg**	**std**	**mad**	**Rsq**	**rho**
ret:	$T_w \cdot A_q$	0.000	0.010***	0.003***	−0.140***	0.084***
	$\hookrightarrow \lvert t \rvert$	1.31	4.69	4.95	7.94	7.21
	Within R^2	0.020	0.309	0.316	0.443	0.417
vol:	$T_w \cdot A_q$	0.066***	0.087***	0.057***	−0.052***	0.066***
	$\hookrightarrow \lvert t \rvert$	5.36	7.76	5.53	9.38	10.32
	Within R^2	0.266	0.414	0.293	0.511	0.548
trn:	$T_w \cdot A_q$	0.054***	0.094***	0.056***	−0.086***	0.083***
	$\hookrightarrow \lvert t \rvert$	4.75	9.15	8.19	10.72	11.69
	Within R^2	0.215	0.506	0.452	0.512	0.567

in means. Following Roth et al. (2022), we employ a two-way-fixed-effects (TWFE) specification described by

$$\Xi_{l,q,w,x} = \beta_{0,l,x} \cdot T_w \cdot A_q + \beta_{1,l,x} + \zeta_{w,l,x} + \xi_{q,l,x} + \varepsilon_{l,q,w,x} \tag{12}$$

with ζ, ξ event and quarter fixed-effects, respectively. The TWFE specification deals with heterogeneity in both the event and time dimensions more precisely than the basic pooled specification. We report the results from the TWFE specification, but results are nearly identical when using the basic specification.

Table 1 presents the results of a set of DiD tests for the US locale, with a cutoff date of $\tilde{q}_{US} = 1Q2001$, the date of promulgation of RegFD. The table presents the results for the five aggregation measures in equation (9) of our three outcome variables: return, volume, and turnover. Panel (a) presents the result using our default definition of "news days"—EADs. Panel (b) repeats, but when "news days" are defined using Factiva news spikes. With the exception of the *avg* measure for returns, discussed above, all other measures yield highly statistically significant DiD coefficients β_0. Upon inspection, the coefficients

Table 2. SDRs and news day reactions—United States (placebo).

This table repeats the presentation of Table 1 of diff-in-diffs for US data, but in Panel (a) "news days" are defined as FOMC/CPI/PPI announcement days and in Panel (b) "news days" are defined randomly per firm, with each trading day having an independent 4 percent probability of being designated a news day.

Panel (c)—FOMC/CPI/PPI		avg	std	mad	Rsq	rho
ret:	$T_w \cdot A_q$	0.000	0.000	0.000	−0.008	0.004
	$\hookrightarrow \lvert t \rvert$	0.02	0.29	0.61	0.24	0.20
	Within R^2	−0.002	−0.001	0.001	−0.001	−0.001
vol:	$T_w \cdot A_q$	−0.019	−0.002	−0.006	0.001	−0.002
	$\hookrightarrow \lvert t \rvert$	0.84	0.21	0.68	0.29	0.40
	Within R^2	0.002	−0.001	0.001	−0.001	−0.001
trn:	$T_w \cdot A_q$	−0.024	−0.006	−0.008	0.008	−0.008
	$\hookrightarrow \lvert t \rvert$	1.10	0.73	1.22	1.14	1.16
	Within R^2	0.004	0.001	0.005	0.004	0.004
Panel (d) - Random		**avg**	**std**	**mad**	**Rsq**	**rho**
ret:	$T_w \cdot A_q$	0.000	0.000	0.000	0.008	−0.004
	$\hookrightarrow \lvert t \rvert$	0.47	0.23	0.02	0.47	0.46
	Within R^2	0.000	−0.001	−0.002	0.000	0.000
vol:	$T_w \cdot A_q$	0.002	−0.004	−0.003	0.001	−0.001
	$\hookrightarrow \lvert t \rvert$	0.48	0.62	0.80	0.51	0.40
	Within R^2	0.000	0.001	0.002	0.000	−0.001
trn:	$T_w \cdot A_q$	0.003	−0.005	−0.003	0.004	−0.004
	$\hookrightarrow \lvert t \rvert$	0.56	0.82	0.99	0.70	0.76
	Within R^2	0.000	0.003	0.004	0.001	0.002

for *std*, *Rsq*, and *rho* are stable between the two panels, while the coefficients for *avg* and *mad* vary dramatically. The Factiva-based "news day" produces more modest results for *avg* and *mad* measures, though they still remain highly statistically significant. As previously mentioned, the Factiva measure may suffer more from Type 1 errors than the EAD-based measure. The dispersion measures *std*, *Rsq*, and *rho* remain largely unaffected and continue yielding quantitatively similar results despite the remarkably different definition of "news day."

The results in Table 1 are consistent with our Hypotheses 1—4. We observe an increase in the "gap" (measured by positive and significant β_0) in volatility for return, volume, and turnover between news and non-news days after the passage of SDRs in the United States, as well as the inverse relation for R^2 (given by the negative and significant β_0).

We next verify the validity of these results by conducting two placebo tests on the US locale. In the first, we define "news-days" to be days in which systematic (rather than idiosyncratic) news is released to the market. We use FOMC and PPI/CPI announcement days as our news-days for this placebo test, such that, for example, a FOMC meeting day is a news day for all firms in the sample. SDRs concern the flow of information from firms to investors, and this information reflects firm-specific information. We therefore expect to find no significant DiD results in this setup. In a second placebo test, we randomly choose news days per firm and repeat the analysis. Table 2 presents these results. In both placebo tests, none of the fifteen testing settings yield statistically significant results for the DiD coefficients β_0. Note that while statistically insignificant, the coefficient signs for the systematic news days in Table 2 are generally *opposite* those in Table 1. This is in line with the findings of Savor and Wilson (2014), who show that on FOMC and PPI announcement

Table 3. SDRs and news day reactions—EU.

This table repeats the presentation of Table 1, but for the EU locale. Panels (a) and (b) are "news days" based on EAD and Factiva spikes, respectively.

Panel (a)—EADs		avg	std	mad	Rsq	rho
	$T_w \cdot A_q$	0.000	0.012***	0.009***	−0.078*	0.044*
ret:	$\hookrightarrow \|t\|$	0.03	4.80	7.25	2.06	2.12
	Within R^2	−0.002	0.175	0.513	0.023	0.025
	$T_w \cdot A_q$	0.211***	0.074*	0.142***	−0.022*	0.038**
vol:	$\hookrightarrow \|t\|$	3.78	2.31	3.85	2.01	2.75
	Within R^2	0.186	0.048	0.208	0.036	0.067
	$T_w \cdot A_q$	0.237***	0.111***	0.185***	−0.066*	0.076**
trn:	$\hookrightarrow \|t\|$	4.10	3.45	5.45	2.01	2.88
	Within R^2	0.241	0.106	0.356	0.050	0.092
Panel (b) - Factiva spikes		**avg**	**std**	**mad**	**Rsq**	**rho**
	$T_w \cdot A_q$	0.000	0.004*	0.002**	−0.072***	0.043***
ret:	$\hookrightarrow \|t\|$	0.31	1.99	3.00	3.43	3.45
	Within R^2	−0.001	0.093	0.194	0.154	0.162
	$T_w \cdot A_q$	0.011	0.043***	0.013	−0.014*	0.021***
vol:	$\hookrightarrow \|t\|$	0.67	3.44	0.93	2.09	3.55
	Within R^2	0.006	0.134	0.016	0.045	0.148
	$T_w \cdot A_q$	0.023	0.066***	0.040***	−0.049***	0.055***
trn:	$\hookrightarrow \|t\|$	1.64	5.21	4.26	4.89	6.06
	Within R^2	0.037	0.274	0.254	0.213	0.299

days, returns follow asset pricing theory *more* closely, in the sense of *higher* return R^2 on such systematic news days, rather than lower as in the idiosyncratic news days.

Table 3 presents the results of the fifteen DiD tests, but for the EU locale, with a cutoff date of $\tilde{q}_{EU} = 4Q2005$, the MAD promulgation date, and with Panels (a) and (b) based on EADs and Factiva news days, respectively. In Panel (a), depicting our main specification, all measures yield statistically significant DiD coefficients β_0, similar to the US results, though effect magnitudes are somewhat smaller for the EU. For our secondary specification, based on Factiva spikes, we again observe lower coefficients and low statistical significance for the *avg* and *mad* coefficients, while the coefficients for *std*, *Rsq*, and *rho* remain fairly stable between the two panels. The results in Table 3 are again consistent with our Hypotheses 1–4. We observe an increase in the gap in volatility for return, volume, and turnover between news and non-news days after the passage of SDRs in the EU.

Finally, Table 4 presents the results for JP and AU, our placebo locales. As neither locale passed SDRs during our main sample period, we present the results of DiD tests using the EU cutoff date, which is approximately the middle of the sample. The table further presents only the results when analyzing EADs. Results are similarly insignificant when using the Factiva spikes as "news days" and/or when using the US cutoff date for the second difference. With the exception of an increase in return volatility in AU, which is reflected in the *std* and *mad* measures for return but not in the better-normalized *Rsq* or *rho* measures or in any measure over the volume and turnover variables, all other tests for JP and AU remain insignificant. Furthermore, the within-R^2 values of the DiD regressions for JP and AU are an order-of-magnitude lower compared to those for United States and EU, indicating considerably less of the variation in return, volume, and turnover R^2 for JP and AU can be explained by the DiD specification.

Table 4. SDRs and news day reactions—JP and AU.

This table repeats the presentation of Table 1, but for the JP and AU locales in Panels (a) and (b), respectively. "News days" are based on EADs. The before/after cutoff date is the same as for the EU locale.

Panel (a)—JP EADs		avg	std	mad	Rsq	rho
ret:	$T_w \cdot A_q$	0.000	0.001	0.000	−0.048	0.030
	$\hookrightarrow \|t\|$	0.14	0.21	0.24	0.83	0.97
	Within R^2	−0.002	−0.002	−0.002	0.006	0.009
vol:	$T_w \cdot A_q$	−0.026	−0.020	−0.034	0.017	−0.013
	$\hookrightarrow \|t\|$	0.41	0.48	0.90	0.74	0.60
	Within R^2	0.000	0.001	0.008	0.007	0.004
trn:	$T_w \cdot A_q$	0.099	0.027	0.037	−0.022	0.039
	$\hookrightarrow \|t\|$	1.69	0.74	1.19	0.54	1.30
	Within R^2	0.054	0.007	0.022	0.003	0.028
Panel (b) - AU EADs		avg	std	mad	Rsq	rho
ret:	$T_w \cdot A_q$	0.006	0.015*	0.012*	−0.110	0.055
	$\hookrightarrow \|t\|$	1.40	2.04	1.99	1.00	1.03
	Within R^2	0.052	0.143	0.260	0.008	0.009
vol:	$T_w \cdot A_q$	0.177	0.104	0.163	−0.046	0.049
	$\hookrightarrow \|t\|$	1.38	0.70	1.45	0.79	0.78
	Within R^2	0.042	0.012	0.073	0.009	0.010
trn:	$T_w \cdot A_q$	0.245	0.099	0.206	−0.131	0.092
	$\hookrightarrow \|t\|$	1.83	0.73	1.94	1.00	1.07
	Within R^2	0.087	0.014	0.152	0.020	0.019

4.2 Evidence on timing

We next focus on the timing of the observed changes. According to Hypotheses 1–4, we should observe an abrupt shift around the dates of SDR passage.

Figure 1 presents the data for the *Rsq* measure of returns for the US locale. Panel (a) of the figure presents the entire time series of quarterly return R^2 for news days and non-news days, using the EAD definition of news days. News days are days 0 in event time, and non-news days are days $-3,-2,2,3$ in event time, so the panel presents the values of $\Xi_{US,q,(0),r}$ and $\Xi_{US,q,(-3,-2,2,3),r}$ for all q values. The panel also includes local linear kernel regression lines (LLRs), along with their confidence bands, and a vertical line marking the quarter of Reg FD's promulgation.[17] Panel (a) shows that return R^2 was not statistically significantly different between news days and non-news days prior to the passage of RegFD. Put differently, Roll's R^2 puzzle holds in the pre-SDR period. Right around the passage of RegFD, the "gap" between return R^2 on non-news days relative to news days grows, as Hypothesis 2 predicts and Table 1 ascertains. Roll's R^2 puzzle ceases to hold. The figure also visually verifies the parallel-trends assumption, necessary for the validity of the DiD setup.

While the visual evidence presented in Panel (a) of figure 1 is striking, we also provide formal statistical tests to determine the timing of the posited (and evident) structural change in market behavior. To determine the timing of such change, we employ the regime-switching regression method of Hamilton (1989), specifically designed to identify regime switches in time-series data. The regime-switching approach has been used in identifying the impact of government regulatory changes by, for example, Hamilton (1988),

[17] The LLRs use the standard Epanechnikov kernel and a bandwidth of four quarters. We verify that results are robust to the choice of kernel and bandwidth.

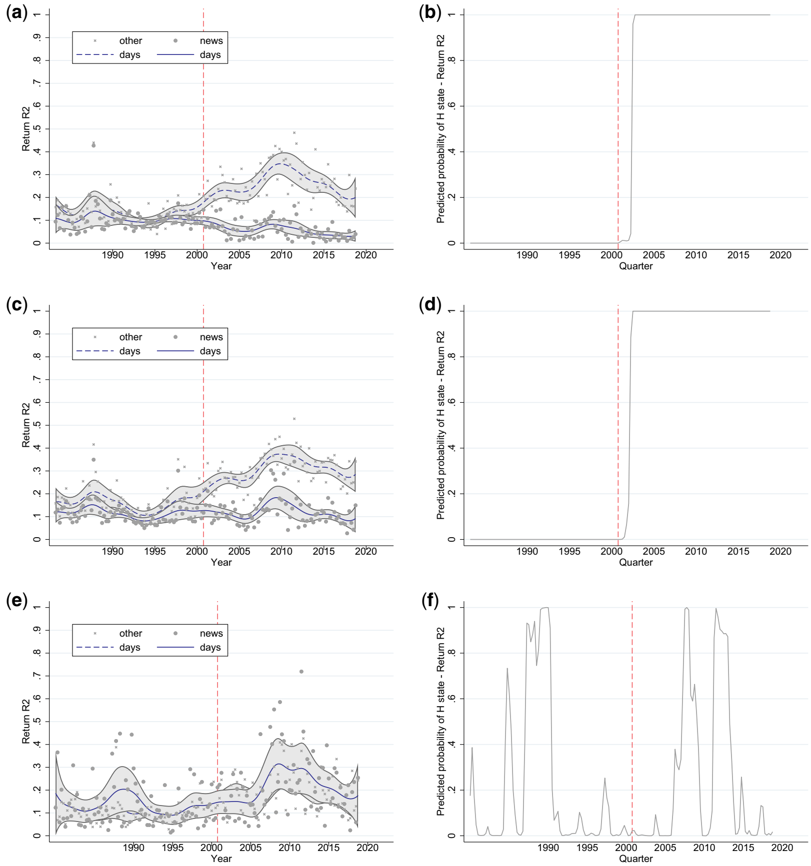

Figure 1. Return R^2—United States. Panel (a) presents the quarterly R^2 of regressing daily return on expected return for Earning Announcement Days (EADs; event day 0) and non-EADs (average of event days −3, −2,2,3), along with a local-linear kernel regression for each and their respective confidence bounds, per quarter for the US locale, and Panel (b) presents the respective predicted state probabilities from a regime-switching regression applied to the quarterly gaps (difference between EADs and non-EADs) in the return R^2. Panels (c) and (d) repeat, but using the Factiva-spike definition of news-days, rather than EADs. Panels (e) and (f) repeat for systematic news days (FOMC and PPI/CPI announcement days). Dashed line marks the date of SDR promulgation in the United States.

Sims and Zha (2006), and Davig (2004). Informally, a regime-switching regression assumes that a process with two states exists in some non-stationary time-series data. Importantly, it does not receive as input the frequency of regime switches or the time at which regime switches occur. Rather, it treats the regime as a two-state hidden Markov process and assumes that the observed data are derived from the Markov process. That is, it estimates the parameters of this hidden Markov process using maximum likelihood. The output of the method is the mean and standard deviation of the observed data during each state, and the Markovian state transfer matrix. The method also yields the likelihood that an observed data point (e.g., the R^2 gap between news-days and non-news days in a given quarter, $\Xi^{Rsq}_{US,q,r}$) is derived from the first or second regime (state).[18] Panel (b) of figure 1 presents the predicted probability of being in a high state (a state with a high R^2 return gap) in the

[18] For more information on regime switching regressions, see Hamilton (1994), chapter 22.

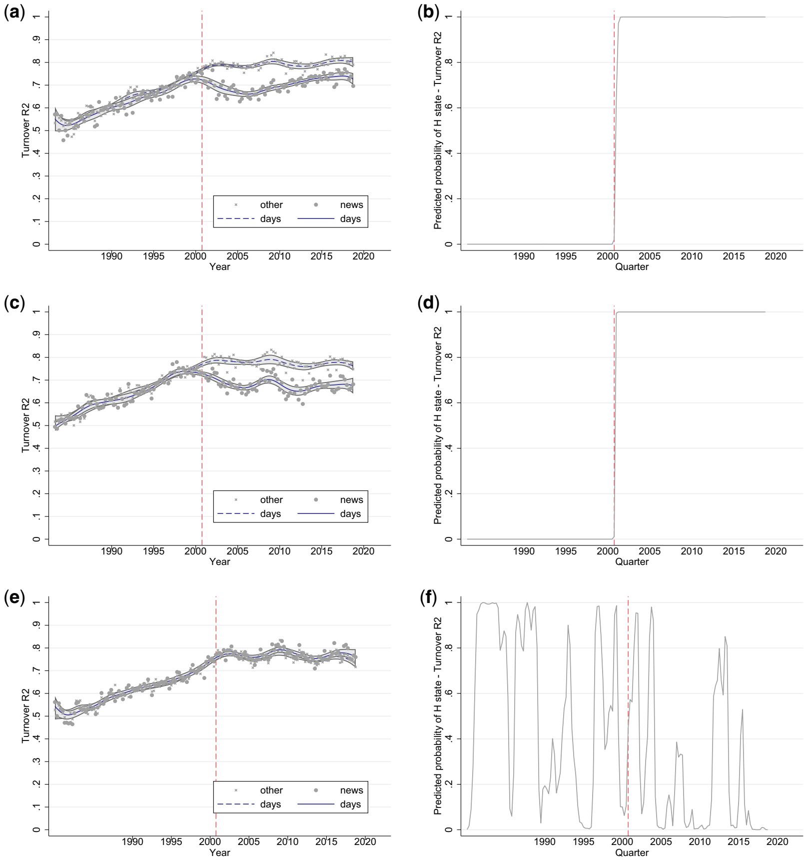

Figure 2. Turnover R^2—United States. Panel (a) presents the quarterly R^2 of regressing daily turnover on expected turnover for EADs (event day 0) and non-EADs (average of event days −3, −2,2,3), along with a local-linear kernel regression for each and their respective confidence bounds, per quarter for the US locale, and Panel (b) presents the respective predicted state probabilities from a regime-switching regression applied to the quarterly gaps (difference between EADs and non-EADs) of the turnover R^2. Panels (c) and (d) repeat, but using the Factiva-spike definition of news-days, rather than EADs. Panels (e) and (f) repeat for systematic news days (FOMC and PPI/CPI announcement days). Dashed line marks the date of SDR promulgation in the United States.

data presented in Panel (a), based on the appropriate regime-switching regression. We observe a sudden and stark regime change, right around the passage of SDRs in the United States.

Panels (c) and (d) repeat this presentation using the Factiva definition of news days rather than EADs. Here too we observe an abruptly increasing "gap" between return R^2 on non-news days relative to news days, right around the passage of RegFD. This is in contrast to the results in Panels (e) and (f), which use the placebo definition of "news days" as FOMC/CPI/PPI days. For those panels, we observe no increase in the gap, sudden or otherwise. As expected, the regime-switching chart in Panel (f) is noisy and inconclusive.

The same results, albeit significantly cleaner, are observed in figure 2, which plots results for turnover R^2. Panel (a) presents the turnover R^2 in the United States during EAD news days and non-news days, and Panel (b) presents the respective regime-switching regression results. The increasing gap hypothesized in Hypothesis 4 is clearly observable, the change is sudden and happens right around the enactment of RegFD, and parallel trends in the

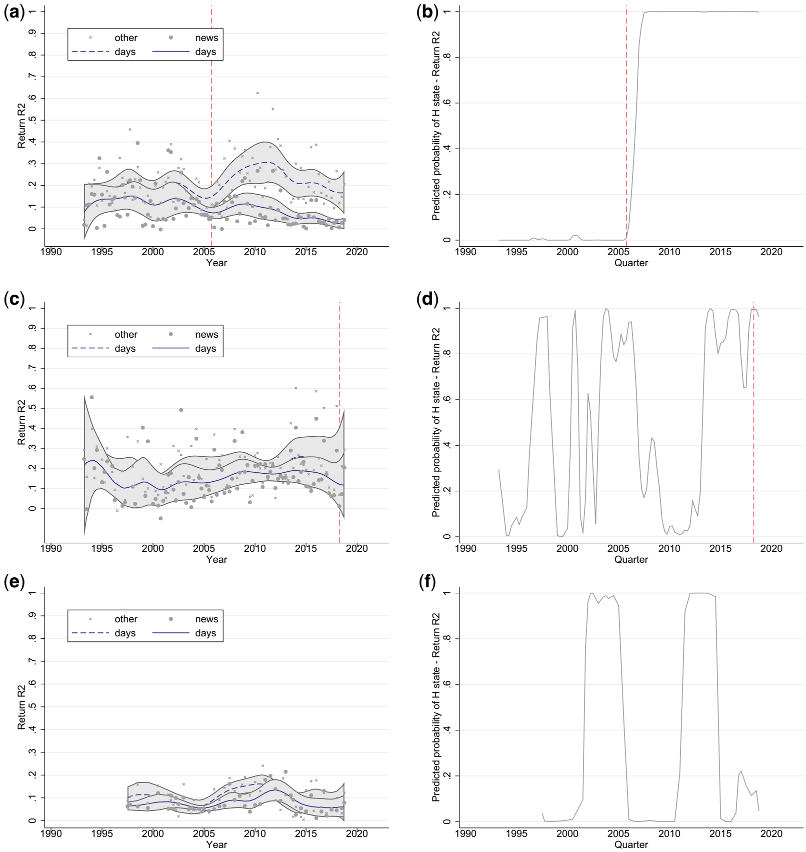

Figure 3. Return R^2—EU, JP, and AU. Panel (a) presents the quarterly R^2 of regressing daily return on expected return for EADs (event day 0) and non-EADs (average of event days −3, −2,2,3), along with a local-linear kernel regression for each and their respective confidence bounds, per quarter for the EU locale, and Panel (b) presents the respective predicted state probabilities from a regime-switching regression applied to the quarterly gaps (difference between EADs and non-EADs) of the return R^2. Panels (c) and (d) repeat for the JP locale and Panels (e), (f) repeat for the AU locale. Dashed line marks the date of the SDR promulgation in the respective locale.

pre-period are evident. Similar results are observed when using the Factiva definition of news days in Panels (c) and (d) of the figure. Finally, the placebo test in Panels (e) and (f) exhibits no difference and no increasing gap between the turnover R^2 on news days versus non-news days when using the placebo systematic news day definition. The turnover variant of Roll's R^2 puzzle holds prior to the enactment of SDRs and ceases to hold after their enactment.

The evidence in figures 1 and 2 exhibits a sharp and persistent change in US market behavior, in a manner consistent with the predicted impact of SDRs and at the same time as the enactment of these SDRs. But many things changed during 2001 in the United States and around the world. Hence, despite the fact that the evidence is consistent with our overall hypothesis that SDRs caused a change in market behavior, it cannot prove the hypothesis.

To make further progress, we go on to present international data. Panel (a) of figure 3 presents the return R^2 data for the EU, which enacted an SDR in 2005, and Panel (b) presents the respective regime-switching chart. Panels (c) and (d) repeat for the JP locale, and Panels (e) and (f) for the AU locale. While the pattern we observed in the United States

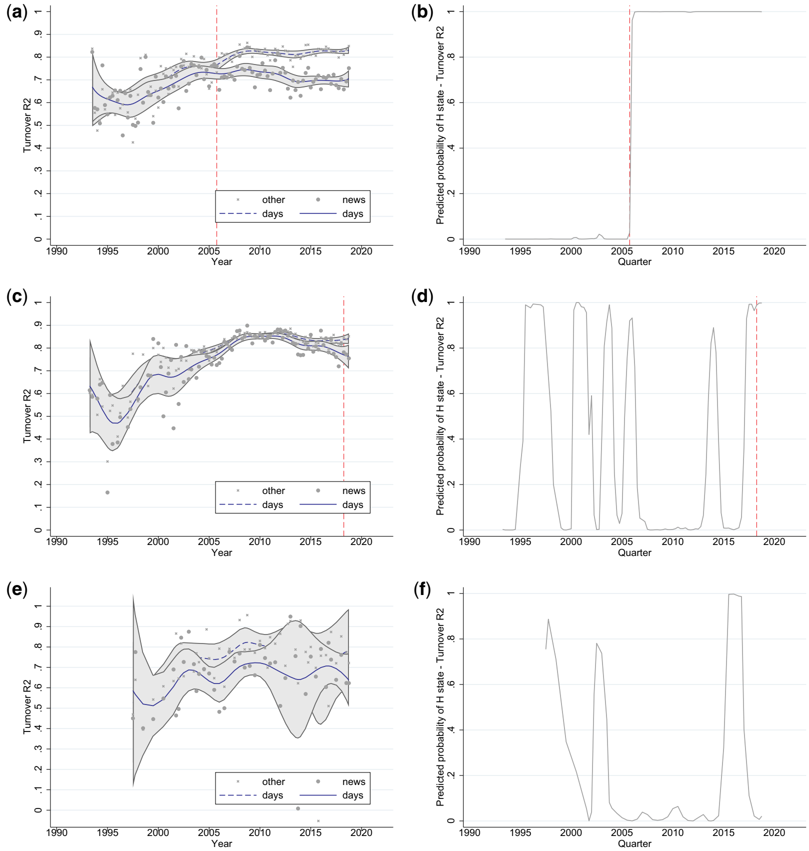

Figure 4. Turnover R^2—EU, JP, and AU. Panel (a) presents the quarterly R^2 of regressing daily turnover on expected turnover for EADs (event day 0) and non-EADs (average of event days −3, −2,2,3), along with a local-linear kernel regression for each and their respective confidence bounds, per quarter for the EU locale, and Panel (b) presents the respective predicted state probabilities from a regime-switching regression applied to the quarterly gaps (difference between EADs and non-EADs) of the return R^2. Panels (c) and (d) repeat for the JP locale, and Panels (e) and (f) repeat for the AU locale. Dashed line marks the date of the SDR promulgation in the respective locale.

in 2001 is evident in the EU in 2005, there is no similar pattern in JP or in AU at any point in the period. Similar results hold when considering turnover R^2 in figure 4. Overall, the evidence shows that US and EU market behavior changed sharply and persistently around the passage of their respective SDRs, in a manner consistent with the predicted impact of SDRs, and at the same time as the enactment of these SDRs. Conversely, no such changes are evident in our placebo (or control) locales.

5. Conclusion

In this article, we develop a theoretical model and provide empirical evidence on the impact of SDRs on financial markets. Our model demonstrates how selective disclosure leads to information asymmetry, resulting in decreased market liquidity and heightened return volatility on non-news days. The introduction of SDRs disrupts this flow of information, thereby shifting return volatility from non-news to news days, more in line with Roll's (1988) intuition in his AFA Presidential Address.

Our empirical analysis, contrasting the effects in the United States and EU with the absence of such changes in JP and AU, supports our model. This is further corroborated by our examination of various outcome variables and various definitions of "news day." We conclude that Roll's failure to find evidence in favor of his prediction was because his sample lies entirely prior to the passage of SDRs. In effect, owing to selective disclosure, "news" was not really news.

The facts we present constitute a high bar for any explanation of the data other than selective disclosure. An alternative explanation would need to account for (1) the symmetric effects in both returns and turnover, (2) why the structural break was observed in the United States in 2001 but in the EU in 2005, and (3) why no structural break was observed in JP or AU, neither of which passed SDRs in our sample period. This list rules out any changes occurring contemporaneously among developed nations, including the emergence of the internet, the rise of passive trading, or the dot com crash.

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Data availability

All data owned by third-party vendors used in this article are available either from Wharton Research Data Services (https://wrdswww.wharton.upenn.edu/) or from Factiva (https://www.dowjones.com). Our institutions purchased or obtained access to these datasets but do not own the data; we cannot share them without written permission from the third-party data providers. Other datasets were derived from sources in the public domain, including the Federal Reserve Bank of St Louis (https://fred.stlouisfed.org/) and Ken French's website (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french)

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Appendix

A. Informed trading with selective disclosure

In this appendix, we present the mathematical details of the model described in Section 2.4. At $t=1$, the IT uses the signal to infer a posterior belief about the liquidation value, denoted $\hat{v}$. Because v and s are normally distributed, we can use the projection theorem used by Kyle, and the IT infers

$$\hat{v} = \mathbb{E}[v|\tilde{v}] = \mathbb{E}[v] + \frac{\mathbb{C}[v,\tilde{v}]}{\mathbb{V}[\tilde{v}]}\cdot(\tilde{v} - \mathbb{E}[\tilde{v}]) = \mu_v + \rho^2\cdot(\tilde{v} - \mu_v) \tag{A.1}$$

with $\mathbb{E},\mathbb{V},\mathbb{C}$ being the expectation, variance, and covariance operators, respectively. Similar to the Kyle model, the amount the IT chooses to trade at $t=1$ can be written as a linear function of the posterior expectation $\hat{v}$ such that $x_1 = X(\hat{v}) = a + b\cdot\hat{v}$, and the price set by the MM for that period can be written as $p_1 = P(y_1) = c + d\cdot y_1$. The IT’s expected profit equals

$$\mathbb{E}[\pi] = \mathbb{E}[x_1\cdot(v - p_1)] = x_1\cdot(\hat{v} - \mathbb{E}[p_1]) = x_1\cdot(\hat{v} - (c + d\cdot x_1)) \tag{A.2}$$

To maximize profit, the IT chooses x_1 by taking the derivative of $\mathbb{E}[\pi]$ with respect to x_1 and setting it equal to zero. This yields the optimal quantity

$$\begin{aligned} x_1 &= \frac{\hat{v} - c}{2\cdot d} = a + b\cdot\hat{v} \\ &\Rightarrow\; b = 1/(2\cdot d)\;;\; a = -c/(2\cdot d) \end{aligned} \tag{A.3}$$

and the expected optimal profit

$$\mathbb{E}[\pi] = \frac{(\hat{v} - c)^2}{4\cdot d} \tag{A.4}$$

which depend on the parameters c, d determined by the MM.

The MM, in turn, solves a problem similar to that of the IT, in which it attempts to infer information on x_1 and hence $\hat{v}$ from the noisy observation of total trade volume $y_1 = x_1 + u_1 = a + b \cdot \hat{v} + u_1$. Because $v, \hat{v}$ and u_1 are normally distributed, we can again apply the projection theorem and the MM sets

$$p_1 = \mathbb{E}[v|y_1] = \mathbb{E}[v] + \frac{\mathbb{C}[v, y_1]}{\mathbb{V}[y_1]} \cdot (y_1 - \mathbb{E}[y_1]) \tag{A.5}$$

Simplifying and noting that $\sqrt{\mathbb{V}[\hat{v}]} = \sqrt{\mathbb{C}[v, \hat{v}]} = \rho \cdot \sigma_v$ (From the IT's perspective $\sigma_{\hat{v}} = \sqrt{1-\rho^2} \cdot \sigma_v = \rho \cdot \sigma_s$, because the IT knows $\hat{v}$) this becomes

$$\begin{aligned} p_1 &= \mu_v + \frac{b \cdot \rho^2 \cdot \sigma_v^2}{b^2 \cdot \rho^2 \cdot \sigma_v^2 + \sigma_u^2} \cdot (y_1 - a - b \cdot \mu_v) = c + d \cdot y_1 \\ &\Rightarrow \ d = \rho \cdot \sigma_v / 2 \cdot \sigma_u \ ; \ c = \mu_v \\ &\Rightarrow \ b = \sigma_u / \rho \cdot \sigma_v \ ; \ a = \ -\mu_v \cdot \sigma_u / \rho \cdot \sigma_v \end{aligned} \tag{A.6}$$

Finally, denoting the Z-transform

$$z_{\hat{v}} = (\hat{v} - \mathbb{E}[\hat{v}]) / \sqrt{\mathbb{V}[\hat{v}]} = (\hat{v} - \mu_v) / \rho \cdot \sigma_v \sim \mathbb{N}(0, 1) \tag{A.7}$$

we can substitute the values we found for a, b, c, d and simplify terms. The policies and the IT's expected profit are then

$$\begin{aligned} p_1 &= \mu_v + \frac{\rho \cdot \sigma_v}{2 \cdot \sigma_u} \cdot y_1 \\ x_1 &= z_{\hat{v}} \cdot \sigma_u \\ \mathbb{E}[\pi] &= \frac{z_{\hat{v}}^2 \cdot \rho \cdot \sigma_v \cdot \sigma_u}{2} \end{aligned} \tag{A.8}$$

The claims in equation (3) follow.

Next, we extend the model to allow the IT to purchase information. Specifically, the IT begins period $t = 0$ with a signal of quality ρ_0, representing information acquired via selective disclosure. The IT can then acquire further information and choose an optimal signal quality $\rho \in [\rho_0, 1)$ subject to a cost function $\Gamma(\rho) \geq 0$ incurred at $t = 0$. The expected profit for a given choice of signal quality ρ is then

$$\mathbb{E}_0[\pi|\rho] = \frac{\rho \cdot \sigma_v \cdot \sigma_u}{2} - \Gamma(\rho) \tag{A.9}$$

Several assumptions on the shape of the cost function Γ are merited. First, we assume the IT can always choose to forego becoming further informed, hence $\Gamma(\rho \in [0, \rho_0]) \equiv 0$. Second, we assume being completely informed about the company is infinitely difficult, so $\Gamma(\rho \to 1) \to \infty$. Finally, we assume convexity of $\Gamma(\rho_0 < \rho < 1)$, so the first two derivatives of the cost function on this range are positive. An example valid cost function is

$$\Gamma(\rho) = f \cdot \frac{\rho - \rho_0}{1 - \rho} \tag{A.10}$$

with $f > 0$ a convex cost parameter known to all.

Table A1. Contemporaneous correlations.

This table presents the cross-correlations between Factiva news shocks ($\varepsilon_{s,i,t} = s_{i,t} - \mathbb{E}^{arma}[s_{i,t}]$), turnover shocks ($\varepsilon_{u,i,t} = u_{i,t} - \mathbb{E}^{arma}[u_{i,t}]$), and absolute return shocks ($\varepsilon_{r,i,t} = |r_{i,t} - \mathbb{E}^{ff}[r_{i,t}]|$), by event-day for event-days −3 to 3, based on the Factiva-spike event-day definition. Panel (a) presents the results for the United States and Panel (b) for the EU.

Panel (a)—United States	–3	–2	–1	0	1	2	3
ε_s vs. ε_r	0.0296	0.0249	0.0423	0.1752	0.0541	0.0250	0.0256
ε_s vs. ε_u	0.0327	0.0334	0.0506	0.1998	0.0574	0.0376	0.0329
ε_r vs. ε_u	0.2314	0.2342	0.2825	0.4047	0.2939	0.2135	0.2140
Panel (b)—EU	**–3**	**–2**	**–1**	**0**	**1**	**2**	**3**
ε_s vs. ε_r	0.0381	0.0337	0.0569	0.2020	0.0584	0.0368	0.0445
ε_s vs. ε_u	0.0428	0.0465	0.0734	0.2395	0.0594	0.0543	0.0467
ε_r vs. ε_u	0.2004	0.2031	0.2713	0.4102	0.2174	0.1945	0.1912

Table A2. Shifted correlations.

This table presents the cross-correlations between Factiva news shocks, turnover shocks, and absolute return shocks, between the day 0 value of one and the days (–1,0,1) values of the other, based on the Factiva-spike event-day definition. Panel (a) presents the results for the United States, and Panel (b) for the EU.

Panel (a)—United States	–1	0	1
ε_s vs. ε_r	0.0338	0.1752	0.0815
ε_s vs. ε_u	0.0510	0.1998	0.0459
ε_r vs. ε_u	0.0824	0.4047	–0.0103
Panel (b)—EU	**–1**	**0**	**1**
ε_s vs. ε_r	0.0138	0.2020	0.0417
ε_s vs. ε_u	0.0412	0.2391	0.0196
ε_r vs. ε_u	0.0667	0.4102	–0.0042

For a participating IT which chooses $\rho > \rho_0$, maximum expected profit is obtained when the marginal cost of increasing ρ equals the marginal benefit,

$$\frac{\partial \Gamma(\rho)}{\partial \rho} = \frac{\sigma_v \cdot \sigma_u}{2} \tag{A.11}$$

and the IT will become further informed if expected profit at this precision level is higher than at ρ_0. For the example function, this would be

$$\rho = 1 - \sqrt{\frac{2 \cdot f \cdot (1 - \rho_0)}{\sigma_v \cdot \sigma_u}} \tag{A.12}$$

Note that

$$\frac{d\rho}{d\rho_0} = \sqrt{\frac{f}{2 \cdot \sigma_v \cdot \sigma_u \cdot (1 - \rho_0)}} > 0 \tag{A.13}$$

This comparative static result demonstrates that decreasing selective disclosures results in a net decrease in the overall information available in the market. This is because, even though traders may try to offset the scarcity of tip-off information by buying more, their efforts do not fully compensate for the absence of freely provided information, leading to lower total information availability in period 1.

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