

It is Imperative to Perform Event Studies Only
With High-Frequency Intraday Data for Securities
Litigations and Valuations^{1,2,3}

Rajeev R. Bhattacharya, Ph.D.^{4,5} Joseph J. Bial, J.D., Ph.D.⁶

Alex J. Evans⁷

October 6, 2023

¹Forthcoming, *Journal of International Business & Law*.

²The views and findings set forth herein are solely those of the authors.

³We are grateful to Reena Aggarwal, Matt Armstrong, Ray Ball, Michael McDonald, Vikram Nanda, Jeffrey Pontiff, Lei Shi, Raghu Sundaram, Erik Sirri, Simon Wheatley, Hamid Yahyaei, seminar and conference participants at Warsaw School of Economics, Macquarie University, St. Mary's University, University of Texas, University of Auckland, and the Securities and Exchange Commission, and especially Tom Smith, Ahmed Elnahas, Siamak Javadi, Robert Korajczyk, Pete Kyle, Mahendra Gupta, and Glenn MacDonald.

⁴Corresponding author.

⁵President, Washington Finance and Economics; RRB.WashingtonFinance@gmail.com.

⁶Partner, Paul, Weiss, Rifkind, Wharton & Garrison; JBial@PaulWeiss.com.

⁷Senior Associate, Macfarlanes; Alex.Evans@Macfarlanes.com.

Abstract

We provide an overview of the legal framework for the analysis of market efficiency in securities class actions. Analyzing all publicly traded U.S. stocks for 2014 - September 2021, using intraday data from TAQ, TRACE, I/B/E/S, and Capital IQ, using daily data from CRSP, Compustat, CRSP-Compustat Merged Database, and FRED, we find that all reaction, overreaction, correction, overcorrection, bounceback, etc., for equities, are systemically all out of the system within two hours after a potentially material event. Therefore, it is imperative to use high-frequency intraday data for event studies and market efficiency work, in the case of every securities litigation and valuation. We compile a dataset of systematic, independent, and objective characterizations of each ticker-year, ticker-halfyear, ticker-quarter, and ticker-month, and each year, halfyear, quarter, and month, 2014 - September 2021, as statistically and economically significant efficient, statistically and economically significant inefficient, or otherwise. We find that *Cammer Factors* and other previous work in securities litigation using daily data and/or *ad hoc* subjective judgments are unreliable.

Keywords: Market efficiency; Intraday data; Event studies; Earnings announcements; Key developments; Securities class actions; Big Data in finance.

JEL Codes: K22; G14; G18.

1 Introduction

In this paper, we prove that:

1. It is imperative to use intraday data for event studies work: 1) systemically, two hours are sufficient to measure the impact of a potentially material event in question, and 2) if one were to use daily data, one would miss the impact of an event that reverts quickly, and/or worse yet, one could erroneously attribute the impact of entirely unrelated events to the potentially material event in question;
2. Event studies using *ad hoc* subjective judgments on whether an event (such as an analyst report) is better than expected news, worse than expected news, or no surprise at all, are fatally flawed (and have been strongly criticized by courts), because there is no objective and systematic way to determine from publicly available data what the markets expected at a particular point of time; and
3. Therefore, work using daily (or lower frequency) data and/or *ad hoc* subjective judgments is unreliable.

Since Eugene Fama, Lawrence Fisher, Michael Jensen and Richard Roll, “The Adjustment of Stock Prices to New Information,” *International Economic Review*, 1969, and Ray Ball and Philip Brown, “An Empirical Evaluation of Accounting Income Numbers,” *Journal of Accounting Research*, 1968, “hundreds of event studies have been conducted in the legal, financial economics, and accounting literatures...

They test the impact, speed, and unbiasedness of the market’s reaction to an event,” as pointed out by S.P. Kothari, “Capital markets research in accounting,” *Journal of Accounting and Economics*, 2001. Ray Ball, “Fama, Fisher, Jensen, and Roll (1969) — Retrospective Comments,” in John Cochrane and Tobias Moskowitz, eds., *The Fama Portfolio*, Chicago, IL: University of Chicago Press, 2017, provides a retrospective by one of the cofounders of event studies describing the contributions of the other cofounders, and please see Jerold Brown and Stephen Warner, “Using daily stock returns: The case of event studies,” *Journal of Financial Economics*, 1985, for a summary of event studies using daily data, and please see Section 2 for detailed descriptions of event studies using high-frequency intraday data.

To motivate this paper, consider the following example: On September 18, 2018, at 11:42 AM U.S. Eastern, Bloomberg announced that “Tesla Inc. is under investigation by the Justice Department over public statements made by the company and Chief Executive Officer Elon Musk, according to two people familiar with the matter. The criminal probe is running alongside a previously reported civil inquiry by securities regulators.”¹ In Table 0, the “halfhour”² where the announcement took place and the following halfhour are marked in pink, the following halfhours that saw substantial absolute returns ($> 1\%$) are in yellow, and the following halfhours where there were negligible absolute returns are in green, and as suggested by the following

¹<https://www.bloomberg.com/news/articles/2018-09-18/tesla-is-said-to-face-u-s-criminal-probe-over-musk-statements>.

²We divide each trading day into 15 “halfhours” as follows: halfhour 0 for prior to 9:30 AM U.S. Eastern, halfhours 1-13 for each half-hour of the trading hours 9:30 AM - 4 PM U.S. Eastern, and halfhour 14 for after 4 PM U.S. Eastern.

table, all reaction, overreaction, correction, overcorrection, bounceback, etc.,³ were almost all out of the system within two hours after the potentially material event.

Table 0				
TSLA Intraday Returns on September 18-19, 2018				
Date	Beginning Time	End Time	VWAP	Halfhourly Return
9/18/2018	11:00 AM	11:30 AM	\$300.80	0.803%
9/18/2018	11:30 AM	12:00 PM	\$285.55	-5.202%
9/18/2018	12:00 PM	12:30 PM	\$282.40	-1.107%
9/18/2018	12:30 PM	1:00 PM	\$279.34	-1.093%
9/18/2018	1:00 PM	1:30 PM	\$284.66	1.887%
9/18/2018	1:30 PM	2:00 PM	\$284.27	-0.137%
9/18/2018	2:00 PM	2:30 PM	\$284.56	0.102%
9/18/2018	2:30 PM	3:00 PM	\$283.04	-0.534%
9/18/2018	3:00 PM	3:30 PM	\$284.55	0.532%
9/18/2018	3:30 PM	4:00 PM	\$284.37	-0.062%
9/18/2018	4:00 PM	11:59 PM	\$285.05	0.236%
9/19/2018	12:00 AM	9:30 AM	\$281.32	-1.315%
9/19/2018	9:30 AM	10:00 AM	\$284.90	1.263%
9/19/2018	10:00 AM	10:30 AM	\$286.03	0.397%
9/19/2018	10:30 AM	11:00 AM	\$288.83	0.973%
9/19/2018	11:00 AM	11:30 AM	\$290.37	0.533%
9/19/2018	11:30 AM	12:00 PM	\$289.52	-0.294%
9/19/2018	12:00 PM	12:30 PM	\$292.12	0.896%
9/19/2018	12:30 PM	1:00 PM	\$293.88	0.600%
9/19/2018	1:00 PM	1:30 PM	\$293.90	0.006%
9/19/2018	1:30 PM	2:00 PM	\$292.78	-0.381%
9/19/2018	2:00 PM	2:30 PM	\$294.37	0.542%
9/19/2018	2:30 PM	3:00 PM	\$296.35	0.671%
9/19/2018	3:00 PM	3:30 PM	\$298.39	0.683%
9/19/2018	3:30 PM	4:00 PM	\$298.74	0.117%
9/19/2018	4:00 PM	11:59 PM	\$298.99	0.083%

³For this motivating example, we use the actual absolute returns, not the absolute abnormal returns that we describe later.

As in Rajeev Bhattacharya, *Uncertainty and Risk, Theory and Empirics: With Applications to Big Data in Finance*, World Scientific, London, 2023 (forthcoming), analyzing all publicly traded U.S. stocks for 2014 - September 2021, using intraday data from TAQ, TRACE, I/B/E/S, and Capital IQ, and using daily data from CRSP, Thomson Reuters, Compustat, CRSP-Compustat Merged Database, and FRED, (tens of trillions of observations,⁴ about 30 TB of data⁵), we find, with robust econometrics, that all reaction, overreaction, correction, overcorrection, bounceback, etc., are systemically all out of the system within two hours after a potentially material event, for all equities — of course, some events have longer horizons, but that is the nature of idiosyncrasies versus a strongly persuasive systemic result. Therefore, it is imperative to use intraday data for event studies work: 1) two hours are systemically sufficient to measure the impact of a potentially material event in question, and 2) if one were to use daily data, one would miss the impact of an event that reverts quickly, and/or worse yet, one could erroneously attribute the impact of entirely unrelated events to the potentially material event in question.⁶ Thus, all previous event studies and market efficiency work using daily data, while of enormous and groundbreaking significance in the past, have only historical value now. A potentially material event is systematically and objectively determined separately as 1) a “key development” (identified by S&P Global CapitalIQ, event types include earnings,

⁴For perspective, the total number of stars in the Milky Way is estimated to be 100 billion, less than a hundredth of the number of observations analyzed in this article.

⁵Analyzing Big Data is not a scalable version of the programming that is done for smaller datasets.

⁶Please see, for instance, Edward Xuejun Li, K. Ramesh, Min Shen and Joanna Shuang Wu, “Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-hour and After-hours Revisions,” *Journal of Accounting Research*, 2015.

dividends, mergers & acquisitions, buybacks, public offerings, management changes, debt defaults, dividend cancellations, and regulatory agency inquiries, sourced from regulatory filings and news vendors),⁷ and 2) an earnings announcement or revision, or analyst forecast or revision. The above result relies upon event studies controlling for intraday market equity returns, Nasdaq listing equity returns, industry (3-digit NAICS Code) equity returns, market cap decile equity returns, intraday volatility decile equity returns, dividend decile equity returns, Fama-French factor⁸ decile equity returns, fixed income yield, and daily risk-free and foreign exchange rates,⁹ and uses controlled contrasts between halfhour-level absolute abnormal returns in post-window halfhours on one hand versus control halfhours (non-announcement and non-relevant halfhours) on the other, measured by using the coefficients of one-, two-, and three-way fixed effects in the regression of halfhour-level absolute abnormal returns on tickers, time periods, and interactions, detailed in Section 4.3.¹⁰

A market is *semistrong efficient* if prices reflect all publicly available information and, therefore, a market is efficient if “stock prices adjust very rapidly to new information.” Prices of securities adjust, *albeit* to varying extents, to new information, therefore, markets for securities are efficient in varying degrees — often referred to as *relative efficiency*. In this paper, we use two different metrics — based upon a)

⁷[https://www.marketplace.spglobal.com/en/datasets/key-developments-\(15\)](https://www.marketplace.spglobal.com/en/datasets/key-developments-(15))

⁸See Eugene Fama and Kenneth French, “A five-factor asset pricing model,” *Journal of Financial Economics*, 2015, Eugene Fama and Kenneth French, “Common risk factors in the returns on stocks and bonds,” *Journal of Financial Economics*, 1993, and Eugene Fama and Kenneth French, “The Cross-Section of Expected Stock Returns,” *Journal of Finance*, 1992.

⁹Please see Section 4 for details.

¹⁰Please see William Greene, *Econometric Analysis*, Upper Saddle River, NJ: Pearson, 2018, Jeffrey Wooldridge, *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press, 2010, and John Campbell, Andrew Lo and A. Craig MacKinlay, *The Econometrics of Financial Markets*, Princeton, NJ: Princeton University Press, 1997, for details.

abnormal responses to “key developments” (as indicated by S&P Global) and b) earnings announcements and revisions, and analyst forecasts and revisions, based upon event studies, controlling for intraday market equity returns, Nasdaq listing equity returns, industry (3-digit NAICS Code) equity returns, market cap decile equity returns, intraday volatility decile equity returns, dividend decile equity returns, Fama-French factors, decile equity returns, fixed income yield, and daily risk-free and foreign exchange rates, with intraday data for equity, fixed income securities, earnings announcements and revisions, and analyst forecasts and revisions, on all publicly traded U.S. companies over 2014 - September 2021): a controlled contrast between absolute abnormal returns for relevant halfhours versus absolute abnormal returns in control halfhours (non-announcement and non-relevant halfhours) — measured by the negative of the coefficient of the fixed effect of the interaction between the indicator variable, and as the case maybe, ticker and/or time period of interest, in the regression of halfhour-level absolute abnormal returns on tickers, time periods, and interactions — provides an objective, systematic and ordinal *per se* measure of market efficiency. Following Rajeev Bhattacharya, *Uncertainty and Risk, Theory and Empirics: With Applications to Big Data in Finance*, World Scientific, London, 2023 (forthcoming), we use the Gaussian cumulative likelihood of the Z -score of each variable (except for an indicator or time variable), this makes the impacts comparable and thus, allows a systematic and objective definition of economic significance, which is different from statistical significance.¹¹

¹¹Pretty much everything is statistically significant when working with huge datasets.

Section 2 reviews the literature. Section 3 describes the data. Section 4 describes the event studies. Section 5 summarizes the legal framework for analysis of market efficiency in securities class actions. Section 6 describes the econometric methodology and empirical results of this paper; Table 1 summarizes the fixed effects of post-window halfhours versus control halfhours. Section 7 concludes, and the Appendix provides detailed summary statistics and calculations. Systematic, independent, and objective characterizations of each ticker-year, ticker-halfyear, ticker-quarter, and ticker-month, and each year, halfyear, quarter, and month, 2014 - September 2021, as statistically and economically significant efficient, statistically and economically significant inefficient, or otherwise, are available upon request from the corresponding author.

2 Literature Review

The study of how quickly prices react to new information has a distinguished history, and more recently, insightful research has been done using high-frequency intraday data, here is a brief review, in reverse chronological order. Charles Martineau, “Rest in Peace Post-Earnings Announcement Drift,” *Critical Finance Review*, 2022, concludes that “in modern financial markets, stock prices fully reflect earnings surprises on the announcement date, leading to the disappearance of post-earnings announcement drifts.” Vincent Grégoire and Charles Martineau, “How Is Earnings News Transmitted to Stock Prices?,” *Journal of Accounting Research*, 2022, find that “the best quote instantly adjusts to earning surprises.” Aman Saggu, “The in-

traday bitcoin response to tether minting and burning events: Asymmetry, investor sentiment, and ‘whale alerts’ on Twitter,” *Finance Research Letters*, 2022, finds that “Bitcoin responds positively to ... minting events over 5- to 30-minute event windows, but this response begins declining after 60 minutes.” Jonathan Rogers, Douglas Skinner, and Sarah Zechman, “Run EDGAR Run: SEC Dissemination in a High-Frequency World,” *Journal of Accounting Research*, 2017, find that “prices, volumes, and spreads respond to the news contained in filings beginning around 30 seconds before public posting.” Eric Budish, Peter Cramton, and John Shim, “The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response,” *Quarterly Journal of Economics*, 2015, “use millisecond-level direct-feed data from exchanges to document a series of stylized facts about how the continuous market works at high-frequency time horizons: (i) correlations completely break down; which (ii) leads to obvious mechanical arbitrage opportunities; and (iii) competition has not affected the size or frequency of the arbitrage opportunities.” Edward Li, K. Ramesh, Min Shen and Joanna Wu, “Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-hour and After-hours Revisions,” *Journal of Accounting Research*, 2015, state that their “analysis of the regular-hour recommendation revisions shows large preannouncement returns and trading volume in the [-1 day, -21 minute] window although [they] also find statistically and economically significant returns and trading volume in the announcement window [-20 minute, +20 minute] and in the postannouncement window [+21 minute, +1 day]. In contrast, [their] analysis of the after-hours revisions shows that most of the price and volume reactions occur in the postannouncement window.”

Christine Jiang, Tanakorn Likitapiwat and Thomas McInish, “Information Content of Earnings Announcements: Evidence From After-Hours Trading,” *Journal of Financial and Quantitative Analysis*, 2012, find that “a significant portion of the price change and price discovery occurs immediately after the earnings releases.” Dawn Matsumoto, Maarten Pronk, and Erik Roelofsen, “What Makes Conference Calls Useful? The Information Content of Managers’ Presentations and Analysts’ Discussion Sessions,” *The Accounting Review*, 2011, use “intra-day trading data to calculate absolute returns during each segment. ... [They] first examine the incremental information content of each segment of the call and find that both the presentation and discussion have incremental information content over the accompanying press release. However, [they] find statistically greater abnormal absolute returns during the discussion portion of the call relative to the presentation.” Oya Altinkılıç and Robert Hansen, “On the Information Role of Stock Recommendation Revisions,” *Journal of Accounting and Economics*, 2009, “measure revision returns using narrow return intervals around daytime revision announcements ... for identifying daytime dividend announcement returns from other event returns. [They] find the mean 40 minutes revision announcement returns are economically unimportant ... These results are robust to wider windows of one hour and two hours.” Tarun Chordia, Richard Roll and Avanidhar Subrahmanyam, “Evidence on the speed of convergence to market efficiency,” *Journal of Financial Economics*, 2005, find that for actively traded NYSE stocks, in “thirty minutes, they are well along on their daily quest.” Jeffrey Busse and T. Clifton Green, “Market efficiency in real time,” *Journal of Financial Economics*, 2002, “analyze 322 stocks featured on the Morning Call and Midday Call

segments. [They] find that stocks discussed positively experience a statistically and economically significant price impact beginning seconds after the stock is first mentioned and lasting approximately one minute. The response to negative reports is more gradual, lasting 15 minutes, perhaps due to the higher costs of short selling conclude that prices adjust to stock mentions within fifteen seconds.”

A market is *semistrong efficient* if prices reflect all publicly available information,¹² and, therefore, a market is efficient if “stock prices adjust very rapidly to new information.”¹³ Prices of securities adjust, *albeit* to varying extents, to new information, therefore, markets for securities are efficient in varying degrees — often referred to as *relative efficiency*.¹⁴ Other measures of market efficiency, such as (1) based on securities prices following random walks in efficient markets, used by Charles Cao, Bing Liang, Andrew Lo, and Lubomir Petrusek, “Hedge Fund Holdings and Stock Market Efficiency,” *Review of Asset Pricing Studies*, 2018, and Ekkehart Boehmer and Eric Kelley, “Institutional Investors and the Informational Efficiency

¹²Please see, for example, Eugene Fama, “Efficient Capital Markets: A Review of Theory and Empirical Work,” *Journal of Finance*, 1970, Michael Jensen, “Some Anomalous Evidence Regarding Market Efficiency,” *Journal of Financial Economics*, 1978, Sanford Grossman and Joseph Stiglitz, “On the Impossibility of Informationally Efficient Markets,” *American Economic Review*, 1980, Burton Malkiel, “Efficient Market Hypothesis,” in P. Newman, M. Milgate, and J. Eatwell, eds., *New Palgrave Dictionary of Money and Finance* (Macmillan, London), 1992, Rafael Porta, Josef Lakonishok, Andrei Shleifer, and Robert Vishny, “Good News for Value Stocks: Further Evidence on Market Efficiency,” *NBER Working Paper*, 1995, Larry Harris, *Trading & Exchanges: Market Microstructure for Practitioners* (Oxford University Press), 2003, Tim Loughran and Jay Ritter, “Uniformly Least Powerful Tests of Market Efficiency,” *Journal of Financial Economics*, 2000, Andrei Shleifer, *Inefficient Markets — An Introduction to Behavioral Finance* (Oxford University Press), 2000, Paul Samuelson, “An Enjoyable Life Puzzling Over Modern Finance Theory,” *Annual Review of Financial Economics*, 2009, and Dominik Rosch, Avanidhar Subrahmanyam, and Mathijs Dijk, “The Dynamics of Market Efficiency,” *Review of Financial Studies*, 2017.

¹³Eugene Fama, Lawrence Fisher, Michael Jensen, and Richard Roll, “The Adjustment of Stock Prices to New Information,” *International Economic Review*, 1969.

¹⁴See, for example, John Campbell, Andrew Lo, and A. Craig MacKinlay, *The Econometrics of Financial Markets* (Princeton University Press, Princeton, NJ), 1997.

of Prices,” *Review of Financial Studies*, 2009, (2) the two purely empirical measures of market efficiency based on the asymmetry between positive and negative market returns used by Arturo Bris, William Goetzmann, and Ning Zhu, “Efficiency and the Bear: Short Sales and Markets Around the World,” *Journal of Finance*, 2007, (3) the variance ratio measures of random walk¹⁵ — see John Campbell, Andrew Lo, and A. Craig MacKinlay, *The Econometrics of Financial Markets*, Princeton University Press, Princeton, NJ, 1997 for details, (4) the friction measures of market efficiency — see Kewei Hou and Tobias Moskowitz, “Market Frictions, Price Delay, and the Cross-Section of Expected Returns,” *Review of Financial Studies*, 2005¹⁶ — and (5) the mispricing score based on eleven return anomalies used by Robert Stambaugh, Jianfeng Yu, and Yu Yuan, “Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle,” *Journal of Finance*, 2015, are all **indirect measures** of market efficiency based on a posited positive correlation between each of these indirect measures and the actual efficiency of the market for a security, which is not *per se* relevant but relevant only in the absence of an actual measure of market efficiency. In this paper, we use two metrics, as separate, objective, ordinal, and **actual** *per se* measures of the efficiency of the market for a stock, which eliminates the need for the correlation-based measures referred to above — see Subsection 6.3.

¹⁵The last two methods were also used by Pedro Saffi and Kari Sigurdsson, “Price Efficiency and Short Selling,” *Review of Financial Studies*, 2011.

¹⁶See also Ekkehart Boehmer and Juan (Julie) Wu, “Short Selling and the Price Discovery Process,” *Review of Financial Studies*, 2013.

3 Description of Data

We use data on all publicly traded U.S. stocks for 2014 - September 2021. We use intraday equity trading data from TAQ and intraday fixed income security trading data¹⁷ from TRACE. We restrict attention to stocks corresponding to publicly traded firms that did not have more than one Permno or Ticker or 3-digit NAICS code during 2014 - September 2021. We further restrict attention to stock-days days that did not have splits, reverse splits, or dividends, and to stock-days that have positive closing price and positive shares outstanding and other restrictions, that had the following fields in CRSP: date, closing price, return, shares outstanding, trading volume, closing bid and ask, exchange membership, NAICS code, and had data on the following variables: intraday analyst forecasts and revisions (from I/B/E/S), intraday earnings announcements and revisions (from I/B/E/S),¹⁸ intraday Key Developments (from Capital IQ), daily data from Compustat-CRSP Merged Database, and daily data for T-Bill yields and Nominal Broad U.S. Dollar Index from Federal Reserve of St. Louis (FRED).¹⁹ Summary statistics are available in Table Appendix-1.

4 Event Studies

Since Eugene Fama, Lawrence Fisher, Michael Jensen, and Richard Roll, “The Adjustment of Stock Prices to New Information,” *International Economic Review*, 1969, and Ray Ball and Philip Brown, “An Empirical Evaluation of Accounting Income

¹⁷With $|Yield| \leq 100\%$.

¹⁸With $|Earnings Per Share| \leq \100 .

¹⁹We do not have access to intraday data for treasury yield and foreign exchange rates from FRED; we thank B. Ravikumar for his help on this matter.

Numbers,” *Journal of Accounting Research*, 1968,²⁰ “hundreds of event studies have been conducted in the legal, financial economics, and accounting literatures... They test the impact, speed, and unbiasedness of the market’s reaction to an event,” as pointed out by S.P. Kothari, “Capital markets research in accounting,” *Journal of Accounting and Economics*, 2001.

In this paper, we do *not* ascribe any directional component to any potentially material event, because it is impossible, without additional information or *ad hoc* judgment, to objectively determine the market’s perception prior to any potentially material event and to determine whether a particular potentially material event was better than expected news, worse than expected news, or even a surprise at all. Colloquially speaking: Good news or bad news is not the relevant question here; and it requires subjective judgment to infer from the description of an event if market efficiency would require the price of the security to go up, down, or stay the same. In *Petrobras Securities Litigation*,²¹ the court addressed the issue of directionality and stringently criticized the subjective and *ad hoc* marking of directionality of events in the dueling expert reports — for example, one of the experts in the litigation used the presence or absence of the text “corrupt” in the description of an event to determine the relevant directionality of a potentially material event.

²⁰See Ray Ball, “Fama, Fisher, Jensen, and Roll (1969) — Retrospective Comments,” in John Cochrane and Tobias Moskowitz, eds., *The Fama Portfolio*, Chicago, IL: University of Chicago Press, 2017, for a retrospective by one of the cofounders of event studies describing the contributions of the other cofounders. See Stephen Brown and Jerold Warner, “Using daily stock returns: The case of event studies,” *Journal of Financial Economics*, 1985, for a summary of event studies using daily data.

²¹United States District Court, Southern District of New York, 1:14-cv-09662-JSR, February 2, 2016.

4.1 HalfHour-Level Averages

We use intraday equity trading data from TAQ and intraday fixed income security trading data from TRACE. As discussed earlier calendar-time, rather than transaction-time, is relevant for market efficiency discussions — please see Albert Kyle and Anna Obizhaeva, “Market Microstructure Invariance: Empirical Hypotheses,” *Econometrica*, 2016, for further details. Therefore, We divide each trading day into 15 “halfhours” as follows: halfhour 0 for prior to 9:30 AM U.S. Eastern, halfhours 1-13 for each half-hour of the trading hours 9:30 AM - 4 PM U.S. Eastern, and halfhour 14 for after 4 PM U.S. Eastern. For each stock i , for each trading day, for each halfhour $\tau = \{0, 1, \dots, 14\}$ with positive volume, we calculate the volume-weighted average price (VWAP) of trading prices, and then calculate the relevant continuously compounded return for halfhour τ . We calculate the various weighted averages for equity returns. For each fixed income security Ticker-Cusip, We calculate the volume-weighted average yield (VWAY) and for each Ticker, We calculate the simple average of VWAY over all Cusips corresponding to that Ticker. Since we are using yield-to-maturity (YTM) with traded prices for the FI securities, we have comparability across different coupons, maturities, and periodicities, thus, average yield is meaningful, and we use a simple average to avoid the volatility of ticker-halfhour-yield because of substantially differing trading volumes,²² and we calculate the various weighted averages for FI returns. These calculations are detailed in Technical Appendix A.

²²We are still left with other complexities such as seniority and convertibility, but we do not have these data.

4.2 Market Model

Our market model, detailed in Technical Appendix B, controls for intraday market equity returns, Nasdaq listing equity returns, industry (3-digit NAICS Code) equity returns, market cap decile equity returns, intraday volatility decile equity returns, dividend decile equity returns, Fama-French factor decile equity returns, fixed income yield, and daily risk-free²³ and foreign exchange rates.²⁴ This enables one to predict or benchmark the equity return for that firm i and that halfhour τ — the “normal return” or expected return $\widehat{EqRet}_{i,\tau}$, and therefore, to measure the **abnormal return** $\widehat{AbNEqRet}_{i,\tau} = EqRet_{i,\tau} - \widehat{EqRet}_{i,\tau}$.

4.3 Controlled Contrasts

As detailed in Technical Appendix C, for fixed n announcement halfhours and m relevant halfhours, a systematic and controlled contrast between $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for **Relevant Half Hours** versus $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for **Control Half Hours** would be necessary for an objective, systematic and ordinal direct measure of market efficiency. From the theory, it follows that $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ should be weakly higher for relevant halfhours than for control halfhours, and therefore, in this paper, for each of the identification systems for potentially material events (KD and EA), for each security i , for each quarter t , we provide an ordinal direct **measure of market efficiency** for that security for that quarter as the negative of the coefficient of the interaction

²³Having the risk-free rate as a regressor in the market model is a generalization of using excess return (yield) of security = return (yield) of security minus risk-free rate, in all calculations for equity (fixed income) securities.

²⁴We do not have access to intraday data for foreign exchange rates or T-bill yields.

between the indicator variable for relevant halfhours versus control halfhours, and as the case maybe, ticker and/or time period of interest, in a fixed effects regression of halfhour-level absolute abnormal returns on tickers, time periods, and interactions.²⁵

4.4 Announcement Windows, Relevant Windows, and Post-Event Windows

Depending on how one determines a potentially material event, we have two separate paths of research on event studies. For the first path, we rely upon the marking of an event as a “Key Development” by Capital IQ, a service of S&P Global, to study as a potentially material event for the issuing firm. For each such Key Development for the firm, for each relevant window halfhour following the Key Development, we calculate the absolute abnormal return — we call this the *Key Developments Abnormal Response (KDAR) for that window halfhour following that Key Development*. As mentioned earlier, we do not try to ascribe any directional component to any Key Development, because it is impossible to objectively and systematically determine from publicly available data the market’s perceptions immediately prior to the relevant Key Development and, therefore, it is impossible to objectively and systematically determine whether a particular Key Development was better than expected news, worse than expected news, or just expected.²⁶

²⁵In Rajeev Bhattacharya, “Market Efficiency: A Structural Study with Intraday Data,” *SSRN*, 2023, an objective, systematic and ordinal direct measure of market efficiency is provided by the negative of the positive part of the difference in quarterly means between absolute abnormal returns for relevant halfhours and absolute abnormal returns for control halfhours.

²⁶Even if one were to make an *ad hoc* inference about the directionality of the surprise information in a key development, with errors about market information at the time of a key development, from its description, one would compound error upon error, each of which would be non-identifiable.

The second path studies the impact of earnings announcements and forecasts on security prices and has a long and distinguished history.²⁷ For each earnings announcement, earnings announcement revision, analyst forecast, and analyst forecast revision, we calculate the absolute abnormal return for each relevant window halfhour following the earnings announcement, earnings announcement revision, analyst forecast, and analyst forecast revision — we call this the *Earnings Announcements Abnormal Response (EAAR)* for that earnings announcement, earnings announcement revision, analyst forecast, and analyst forecast revision. Please note that the actual announced EPS or its deviation from “consensus” forecasts do not enter into our calculations; for a number of reasons. Any estimate of the market’s “consensus” prediction of the EPS at the point of an EPS announcement, whether it is by using mean/medians of analyst forecasts, or by using valuation models, is sensitive to the methodology used to estimate the market’s perception and the deviation from it,^{28,29} and therefore, it is impossible to objectively and systematically measure how much

²⁷See, for instance, Ray Ball and Philip Brown, “An Empirical Evaluation of Accounting Income Numbers,” *Journal of Accounting Research*, 1968, Daniel Collins and S.P. Kothari, “An analysis of intertemporal and cross-sectional determinants of earnings response coefficients,” *Journal of Accounting and Economics*, 1989, and S.P. Kothari and Jerold Warner, “Econometrics of Event Studies,” in Espen Eckbo, Ed., *Handbook of Empirical Corporate Finance*, Elsevier/North-Holland, 2007.

²⁸See, for instance, Chin-Han Chiang, Wei Dai, Jianqing Fan, Harrison Hong, and Jun Tu, “Robust Measures of Earnings Surprises,” *SSRN*, 2016, for detailed descriptions of biases in the calculation of deviation from consensus; also please see S.P. Kothari, Eric So, and Rodrigo Verdi, “Analysts’ Forecasts and Asset Pricing: A Survey,” *Annual Review of Financial Economics*, 2016, for a comprehensive survey of the literature on quality, bias, and predictability of earnings forecasts. Treating these analyst forecasts as representing market information at the time of a potentially material event, with forecast errors, would need compounding error upon error, each of which would be non-identifiable.

²⁹The impact of analyst incentives on analyst forecasts is beyond the scope of this paper, see Rajeesh Bhattacharya and Mahendra Gupta, “Diligence, Objectivity, Quality, and Accuracy,” *Journal of Accounting Literature*, 2023, for instance.

information about an actual earnings announcement or forecast leaked out before the actual announcement or forecast, and, therefore, it is impossible to objectively and systematically measure, from publicly available data, the “surprise” component of the earnings announcement or forecast.

For each stock, for each potentially material event at halfhour T , we consider the announcement window halfhours to be $\tau \in \{T, \dots, T + 2 - 1\} = \{T, T + 1\}$ ($n = 2$ halfhours), the relevant window halfhours to be $\tau \in \{T + 1 + 1, \dots, T + 2 + 2 - 1\} = \{T + 2, T + 3\}$ ($m = 2$ halfhours), and the post-relevant windows to be $\tau \in \{T + 2 + 2, \dots, T + 2 + 2 + 6 - 1\} = \{T + 4, \dots, T + 9\}$ ($l = 6$ halfhours).³⁰ We calculate the absolute abnormal return $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for each stock i , for each halfhour τ . As exemplified in Table 0, we find that halfhour-level absolute abnormal returns for the six trading halfhours following each relevant window following each potentially material event (as identified in Subsection 4.4), are not economically significantly higher than all non-announcement and all non-relevant window trading halfhours; i.e., reaction, overreaction, correction, overcorrection, bounceback, etc., are all systemically out of the system within a few hours after a potentially material event, so it is imperative to use intraday data to consider event studies and market efficiency: 1) systemically, two hours are sufficient to measure the impact of a potentially material event in question, and 2) if one were to use daily data, one would miss the impact of an event that reverts quickly, and/or worse yet, one could erroneously attribute the impact of entirely unrelated events to the potentially material event in question.

Therefore, all previous event studies and market efficiency work using daily data,

³⁰Please see Rajeev Bhattacharya and Mahendra Gupta, “Impact of FINRA 2241,” *SSRN*, 2023, for different sensitivities.

while of ground-breaking significance in the past, have only historical value now.³¹

5 Analysis of Market Efficiency in Securities Class Actions — The Legal Framework

Section 10(b) of the Securities Exchange (SEC) Act of 1934 prohibits the “use or employ[ment]” of any “deceptive device” “in connection with the purchase or sale of any security” in breach of rules set out by the Securities and Exchange Commission.³² SEC Rule 10b-5 prohibits entities subject to this Act from “mak[ing] any untrue statement of a material fact” or “omit[ting] to state a material fact necessary in order to make the statements made. . . not misleading.”³³ The courts have inferred from these sources an implied private cause of action permitting the recovery of damages for securities fraud,³⁴ where a plaintiff can prove (among other things) a material misrepresentation or omission by the defendant, and the plaintiff’s reliance on that misrepresentation or omission (the “Reliance Requirement”).³⁵

Several hundred securities class actions are typically filed each year on the above basis.³⁶ Often, defendants will file a motion to dismiss and, roughly half the time, will

³¹Please see the review of the relevant literature in Section 2.

³²15 U.S.C. §78j(b).

³³17 C.F.R. §240.10b-5(b). On a related note, please see the recent article, “SEC Is Focusing on Earnings Manipulation by Companies” (<https://www.wsj.com/articles/sec-is-focusing-on-earnings-manipulation-by-companies-9bc2c592>).

³⁴*Halliburton Co. v. Erica P. John Fund, Inc.*, 573 U.S. 258, 267, 134 S.Ct. 2398, 189 L.Ed.2d 339 (2014) (*Halliburton II*).

³⁵*Ibid.*

³⁶See, e.g., Cornerstone Research, *Securities Class Action Filings: 2022 Year in Review* (page 1), available at <https://www.cornerstone.com/insights/reports/securities-class-action-filings/>. Such cases are predominantly filed in federal court, although they can sometimes be brought in state court pursuant to the Securities Act of 1933.

be successful. Where an action advances beyond a motion to dismiss, the next major hurdle is the class certification hearing, where the court assesses whether the action is appropriate to be brought as a class action, where numerous plaintiffs collectively pursue essentially the same claim against the defendant at the same time, rather than the plaintiffs' claims each proceeding individually to trial. To clear this bar, plaintiffs must demonstrate (among several other requirements) that "the questions of law or fact common to class members predominate over any questions affecting only individual members."³⁷

In relation to the Reliance Requirement, in the context of the court's consideration of predominance at the class certification stage, the courts have established a rebuttable presumption of class-wide reliance (based on the so-called fraud-on-the-market theory that "an investor presumptively relies on a misrepresentation so long as it was reflected in the market price at the time of his transaction"³⁸) where the plaintiffs can prove that: (1) the alleged misrepresentation was publicly known; (2) it was material;³⁹ (3) the stock traded in an efficient market.; and (4) the plaintiff traded the stock between the time the misrepresentation was made and when the truth was revealed (the "*Basic* Presumption"⁴⁰). Defendants can rebut the *Basic* Presumption through "[a]ny showing that severs the link between the alleged misrepresentation and either the price received (or paid) by the plaintiff, or his decision

³⁷Fed. R. Civ. P. 23(b)(3).

³⁸*Erica P. John Fund, Inc. v. Halliburton Co.*, 563 U.S. 804, 813, 131 S.Ct. 2179, 180 L.Ed.2d 24 (2011).

³⁹The Supreme Court has ruled that this particular aspect need not be proved by plaintiffs at the class certification stage and is more appropriately left to the merits stage, since it does not bear on the predominance question. *Amgen Inc. v. Connecticut Retirement Plans and Trust Funds*, 568 U.S. 455, 466-468, 133 S.Ct. 1184 L.Ed. 2d 308 (2013).

⁴⁰*Basic v. Levinson*, 485 U.S. 224, 108 S.Ct. 978, 99 L.Ed.2d 194 (1988).

to trade at a fair market price.”⁴¹ In practice, of the several thousand securities class actions filed since *Halliburton II* in June 2014, there are few occasions where the *Basic* Presumption was rebutted.⁴² As a consequence, the majority of motions for class certification are granted.⁴³ However, the Supreme Court has recently confirmed that, although defendants bear the ultimate burden of persuasion (and not simply an initial burden of production) when attempting to rebut the *Basic* Presumption, a court must consider all evidence relevant to price impact at the class certification stage (including the generic nature of an alleged misrepresentation), even if that evidence is also relevant to a merits question such as materiality.⁴⁴

As regards the third limb of the *Basic* Presumption — market efficiency — one significant decision by the U.S. District Court for the District of New Jersey enumerated several factors that should be considered, including: (1) the average weekly trading volume; (2) the number of security analysts following and reporting on the security; (3) the extent to which market makers traded the security; (4) the issuer’s eligibility to file a U.S. Securities and Exchange Commission registration Form S-3; and (5) the cause-and-effect relationship between material disclosures and changes in

⁴¹ *Ibid.*, at 248, 108 S.Ct. 1978.

⁴² See, e.g., *Ohio Public Employees Retirement System v. Federal Home Loan Mortgage Corp.*, Civ. No. 08-160, 2018 WL 3861840 (N.D. Ohio Aug. 14, 2018); *In Re Finisar Corp. Securities Litigation*, Civ. No. 11-1252, 2017 WL 6026244 (N.D. Cal. Dec. 5, 2017); *In Re Intuitive Surgical Securities Litigation*, Civ. No. 13-1920, 2016 WL 7425926 (N.D. Cal. Dec. 22, 2016); *Erica P. John Fund, Inc. v. Halliburton Co.*, 309 F.R.D. 251 (N.D. Tex. 2015).

⁴³ See, e.g., NERA Economic Consulting, *Recent Trends in Securities Class Action Litigation: 2022 Full-Year Review* (page 12), available at <https://www.nera.com/publications/archive/2023/recent-trends-in-securities-class-action-litigation-2022-full-.html#:~:text=205%20new%20federal%20securities%20class,214%20from%20248%20in%202021>.

⁴⁴ *Goldman Sachs Group, Inc. v. Arkansas Teacher Retirement System, et al.*, 141 S.Ct. 1951, 1960 (2021).

the security's price.⁴⁵ These “*Cammer* Factors” have been adopted by a number of other courts.⁴⁶ Still other courts have added additional considerations. For instance, one court considered the company's market capitalization and the size of the public float for the security,⁴⁷ while another considered the ability to sell short the security and the level of autocorrelation between the security's prices.⁴⁸ A class certification hearing is not a trial on the merits and is often conducted before full discovery is completed, so plaintiffs do not need to prove each of the claim elements on the merits at the class certification stage. But plaintiffs are required to prove — not simply plead — the Rule 23(a) class action requirements and, most typically, that questions of law or fact common to all class members predominate over any questions affecting only individual members. Over the years, tensions have grown, however, as the proof required to establish the class action requirements now frequently spills over into the merits of the underlying claims themselves. The courts are thus struggling to determine what and how much information must be proven during class certification contests. Amid two significant 5-4 decisions reversing class certification decisions because plaintiffs failed to prove the requirements of Rule 23, *Wal-Mart Stores, Inc. v. Dukes*, 564 U.S. (2011) and *Comcast Corp. v. Behrend*, 569 U.S. (2013), the United States Supreme Court has now issued other significant decisions regarding securities class actions cases that ultimately continue to support the 1988 *Basic* decision even

⁴⁵ *Cammer v. Bloom*, 711 F. Supp. 1264, 1286-87 (D. N.J. 1989).

⁴⁶ See *DVI, Inc. Sec. Litig.*, 639 F.3d at 633 n.14; *Teamsters Local 445 Freight Div. Pension Fund v. Bombardier, Inc.*, 546 F.3d 196, 204 n. 11 (2d Cir. 2008); *In re Xcelera.com Sec. Litig.*, 430 F.3d 503, 508 (1st Cir. 2005); *Unger v. Amedisys Inc.*, 401 F.3d 316, 323 (5th Cir. 2005); *Gariety v. Grant Thornton, LLP*, 368 F.3d 356, 368 (4th Cir. 2004); *Binder v. Gillespie*, 184 F.3d 1059, 1064-65 (9th Cir. 1999).

⁴⁷ See *Krogman v. Sterritt*, 202 F.R.D. 467, 478 (N.D. Tex. 2001).

⁴⁸ See *In re Polymedica Corp. Sec. Litig.*, 432 F.3d 1, 18 at n. 21 (1st Cir. 2005).

while demonstrating that the fraud-on-the-market theory and the efficient market theory increasingly are coming under harsh attack. In *Amgen Inc. v. Connecticut Retirement Plans and Trust Funds*, 568 U.S. (2013), a 6-3 majority decided that the materiality requirement of a securities claim was sufficiently distinct from market efficiency and the public nature of securities claims such that it did not have to be established at the class certification stage. The Court reasoned that whether a misrepresentation was sufficiently material to a stock price was certainly a matter of common proof such that the courts do not need to delve into the merits of this issue during class certification. The Court essentially held that, while the parties are presenting event studies that go to the reliance (and the predominance of the common reliance evidence) to show that a stock price effect exists, plaintiffs need not prove during class certification that the stock price effect was material. Although certainly implicit in Justice Scalia’s short dissenting opinion, neither his dissent nor the dissent of Justice Thomas (joined by Justices Scalia and Kennedy) explicitly suggested that the *Basic* decision should be overruled, presumably because that issue was not directly before the Court. *Amgen* is consistent with the Court’s unanimous decision two years earlier in *Erica P. John Fund, Inc. v. Halliburton Co.*, U.S. (2011), which held that plaintiffs need not prove loss causation, that the misrepresentation in question caused the plaintiffs’ economic loss, at the class certification stage. The Fifth Circuit Court of Appeals had previously ruled in favor of Halliburton that plaintiffs’ proof of loss causation, that company statements “actually caused the stock price to fall and resulted in the losses,” was necessary to invoke the *Basic* presumption

of reliance.⁴⁹ Before the Supreme Court, Halliburton also suggested that insufficient evidence existed as to any price impact, thus suggesting there was nothing to rely upon in order to invoke the *Basic* presumption.⁵⁰ The Supreme Court refused to examine the economic evidence and simply concluded that the Court of Appeals erred in conflating loss causation with the reliance element and the *Basic* presumption of reliance.⁵¹ The Court remanded the matter for reconsideration of the trial court's class certification decision. Subsequently, the district court granted class certification, which the Fifth Circuit affirmed.⁵² Halliburton then appealed to the Supreme Court and presented two issues. First and foremost, the Court addressed whether the *Basic* presumption of liability should be overruled, and thus whether plaintiffs should be required to prove actual reliance, including whether class-wide, common proof of reliance was now required at the class certification stage of litigation.⁵³ Second, the Court addressed the extent to which evidence of a presumption of reliance could be rebutted by defendants at the class certification stage, recognizing that class certification hearings are not supposed to be trials on the merits but also recognizing that the Court's recent class action decisions place increasing burdens on plaintiffs to prove (as oppose to presume) the class action requirements of Rule 23.⁵⁴ The Supreme Court yet again unanimously vacated the lower court rulings and instructed the trial court to re-examine the evidence on class certification.⁵⁵ Five

⁴⁹*Erica P. John Fund, Inc. v. Halliburton Co.*, U.S. 131 S.Ct. 2179, 2184 (2011).

⁵⁰*Id.* at 2186.

⁵¹*Id.*

⁵²*Halliburton Co. v. Erica P. John Fund, Inc.*, U.S. 134 S.Ct. 2398, 2406 (2014).

⁵³*Id.*

⁵⁴*Id.* at 2407.

⁵⁵*Id.* at 2417.

justices, led by Chief Justice Roberts, determined that Halliburton should be given an opportunity to rebut the *Basic* presumption of reliance by presenting evidence of a lack of any price impact.⁵⁶ Justices Ginsburg, Breyer and Sotomayor concurred, recognizing that the evidentiary burden of rebutting the *Basic* presumption falls on defendants and thus should not be an additional hurdle for class action plaintiffs.⁵⁷ Justices Thomas, Alito and Scalia concurred in the result but suggested that *Basic* should now be overruled, in part because “‘overwhelming empirical evidence’ now suggests that even when markets do incorporate public information, they often fail to do so accurately” and that “[s]cores’ of ‘efficiency-defying anomalies’ — such as market swings in the absence of new information and prolonged deviations from underlying asset values - make market efficiency ‘more contestable than ever.’”⁵⁸ Thus, the *Basic* presumption remains a fixture of federal securities litigation even though the judicial system is now amply aware of the debates within finance theory about the extent and usefulness of the efficient market hypothesis. Furthermore, the academic debates themselves will certainly carry over into future class certification analyses as *Halliburton* supports defendants’ efforts to garner evidence and present their own event studies challenging the efficiency of the information signals associated with plaintiffs’ allegations of misrepresentations. Without doubt, federal district courts will continue to conduct ever more rigorous reviews of market efficiency at the class certification stage of securities lawsuits. The scope and structure of these analyses are necessarily case-by-case, left to the parties and their financial experts to present evi-

⁵⁶ *Id.*

⁵⁷ *Id.*

⁵⁸ *Id.* at 2421.

dence to the courts, with the courts then making legal determinations about whether the pertinent markets were “efficient enough” to justify the *Basic* presumption of reliance. In this article, we emphasize relative efficiency, that 1) prices of securities reflect, *albeit to varying extents*, all publicly available information, 2) prices adjust, *albeit to varying extents*, to new information, and 3) abnormal returns are close to zero, also *albeit to various extents* — therefore, markets for securities are efficient in varying degrees.⁵⁹

In order to appreciate how trading volume impacts market efficiency, we need to understand why a trade occurs. In particular, “investors trade among themselves because they are different,”⁶⁰ and “volume reflects a lack of consensus regarding the price.”⁶¹ However, there is no reason that higher dispersion in investor valuations necessarily leads to higher market efficiency, and therefore, the impact on market efficiency of normalized trading volume, everything else remaining the same, is fundamentally an empirical question — and the empirical answer is that the efficiency of the market for a stock is *not* significantly and positively affected by trading vol-

⁵⁹See, for instance, *Halliburton Co. v. Erica P. John Fund, Inc.* (Halliburton II), 573 U.S. —, 134 S. Ct. 2398, 2414 (2014), and *Petrobras Securities Litigation*, United States District Court, Southern District of New York, 1:14-cv-09662-JSR, February 2, 2016.

⁶⁰Jiang Wang, “A Model of Competitive Stock Trading Volume,” *Journal of Political Economy*, 1994. See also Jonathan Karpoff, “The Relation Between Price Changes and Trading Volume: A Survey,” *Journal of Financial and Quantitative Analysis*, 1987; Maureen O’Hara, *Market Microstructure Theory*, Blackwell Publishing, Malden, MA, 1997; Scott Stickel and Robert Verrecchia, “Evidence that Trading Volume Sustains Stock Price Changes,” *Financial Analysts Journal*, 1994; Lawrence Blume, David Easley, and Maureen O’Hara, “Market Statistics and Technical Analysis: The Role of Volume,” *Journal of Finance*, 1994; and Edie Hotchkiss, Michael Goldstein, and Erik Sirri, “Transparency and Liquidity: A Controlled Experiment on Corporate Bonds,” *Review of Financial Studies*, 2007.

⁶¹William Beaver, “The Information Content of Annual Earnings Announcements,” *Journal of Accounting Research*, 1968.

ume.⁶² The demand for market making services is an increasing function of trading volume, for instance, through higher dispersion of the valuation profile. As a corollary, everything else remaining the same,⁶³ a firm is more likely to enter (or not exit) the market for market making services if there is higher trading volume (and thus, higher market making profits), for instance, through a higher dispersion of the valuation profile for that security. However, the higher the number of market makers, competition for trades would put downward pressure on the transaction costs, and economies of scale will determine the equilibrium impact on the price of market making services.⁶⁴ Therefore, the direction of the impact of the number of market makers for a security on the efficiency of the market for that security can only be determined empirically — and the empirical answer is that the efficiency of the market for a stock is *not* significantly and positively affected by the number of market makers.⁶⁵ Recent empirical work also shows that short sales costs & constraints do not negatively impact market efficiency.⁶⁶

⁶²See Rajeev Bhattacharya and Stephen O'Brien, "Arbitrage Risk and Market Efficiency — Applications to Securities Class Actions," *Santa Clara Law Review*, 2015; profiled at Stanford University (<http://securities.stanford.edu/resources-academic.html>).

⁶³In particular, keeping constant other incentives of investment banks, such as profits from proprietary trading.

⁶⁴See, for instance, Rajeev Bhattacharya, "Non-Monotonicity of Equilibrium Price," *SSRN*, 2017.

⁶⁵Rajeev Bhattacharya and Stephen O'Brien, "Arbitrage Risk and Market Efficiency — Applications to Securities Class Actions," *Santa Clara Law Review*, 2015; profiled at Stanford University (<http://securities.stanford.edu/resources-academic.html>).

⁶⁶Also see, for instance, Bradford Cornell and James Rutten, "Market Efficiency, Crashes, and Securities Litigation," *Tulane Law Review*, 2006, and Rajeev Bhattacharya and Stephen O'Brien, "Arbitrage Risk and Market Efficiency — Applications to Securities Class Actions," *Santa Clara Law Review*, 2015, for the role of market efficiency in securities litigation. For a description of the importance of relative efficiency for valuations (especially Mark-to-Market) and securities class actions (especially class certification), see Rajeev Bhattacharya, "Objective Measures of Market Efficiency; Applications to Securities Class Actions and Valuations," *Berkeley Business Law Journal*, 2019.

6 Methodology and Empirical Results

6.1 Economic Significance

Following Rajeev Bhattacharya, *Uncertainty and Risk, Theory and Empirics: With Applications to Big Data in Finance*, World Scientific, London, 2023 (forthcoming), when dealing with large numbers of observations, we replace each variable x , except for each indicator or time variable, by its normalization

$$\Phi(Z_Score(x)) = \Phi\left(\frac{x - Mean(x)}{StDev(x)}\right) \sim \mathbb{U}[0, 1]$$

where Φ is the cumulative likelihood function of a standard Gaussian random variable and \mathbb{U} represents a uniform distribution. This is a rigorization of the number of standard deviations approach to interpretation of coefficients, which also implicitly assumes Gaussian distributions. Therefore, all such regression coefficients are comparable, a coefficient $\beta(y, x)$ on the regression of the regressand y on the regressor x means that a 1% increase in the cumulative probability of x is associated with a $\beta(y, x)$ % increase in the cumulative probability of y .⁶⁷

Similarly, a regression coefficient $\beta(y, \mathbf{N})$ on the regression of the regressand y on the indicator variable \mathbf{N} means that there is a $\beta(y, \mathbf{N})$ higher cumulative probability of y for membership in \mathbf{N} , and a regression coefficient $\beta(y, \mathbf{t})$ on the regression of the

⁶⁷It is worth pointing out that $Percentile(x) \simeq RoundUp(100\Phi(Z_Score(x)))$ and, therefore, $|\beta(y, x)| \geq 1$ implies that a move of x to one higher percentile causes y to move up (approximately) $Round(\beta(y, x))$ percentiles, and $0 \leq |\beta(y, x)| < 1$ implies that a move of x to one higher percentile causes y to stay in (approximately) the same percentile. Similarly, $Millenile(x) \simeq RoundUp(1,000\Phi(Z_Score(x)))$, $Decile(x) \simeq RoundUp(10\Phi(Z_Score(x)))$, $Quartile(x) \simeq RoundUp(4\Phi(Z_Score(x)))$, etc.

regressand y on time period \mathbf{t} means that there is a $\beta(y, \mathbf{t})$ increase in cumulative probability of y from one time period to the next.

The impact of a regressor x on the regressand y is **economically significant positive** if the relevant coefficient⁶⁸ $\beta(y, x) > 0.01$ and is **economically significant negative** if the relevant coefficient $\beta(y, x) < -0.01$. We indicate economically significant positive impacts by green highlighting and economically significant negative impacts by red highlighting.

6.2 Fixed Effects

As exemplified in Table 0, and as found in Rajeev Bhattacharya, *Uncertainty and Risk, Theory and Empirics: With Applications to Big Data in Finance*, World Scientific, London, 2023 (forthcoming), using cutting-edge econometrics of one-, two-, and three-way fixed effects in the regression of halfhour-level absolute abnormal returns on tickers, time periods, and interactions, detailed in Section 4.3,⁶⁹ we find in this paper that halfhour-level absolute abnormal returns for the six trading halfhours following each relevant window following each potentially material event (as identified in Subsection 4.4), are not economically significantly higher than all non-announcement and all non-relevant window trading halfhours; i.e., reaction, overreaction, correction, overcorrection, bounceback, etc., are systemically all out of the system within a few

⁶⁸Please see Hiroyuki Aman, Henk Berkman, Tom Smith, et. al., “Responsible science: Celebrating the 50-year legacy of Ball and Brown (1968) using a registration-based framework,” *Pacific Basin Finance Journal*, 2019, for a robust defense of “responsible science,” that science needs to have integrity and relevance.

⁶⁹Please see William Greene, *Econometric Analysis*, Upper Saddle River, NJ: Pearson, 2018, Jeffrey Wooldridge, *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press, 2010, and John Campbell, Andrew Lo and A. Craig MacKinlay, *The Econometrics of Financial Markets*, Princeton, NJ: Princeton University Press, 1997, for details.

hours after a potentially material event; please note that, otherwise, the coefficients for the post-event indicator variables in the fixed effects regressions of halfhour-level absolute abnormal returns would have to be statistically and economically significant — please see Table 1 below. It is, therefore, imperative to use intraday data for event studies and market efficiency work: 1) systemically, two hours are sufficient to measure the impact of a potentially material event in question, and 2) if one were to use daily data, one would miss the impact of an event that reverts quickly, and/or worse yet, one could erroneously attribute the impact of entirely unrelated events to the potentially material event in question.⁷⁰

⁷⁰Please see, for instance, Edward Xuejun Li, K. Ramesh, Min Shen and Joanna Shuang Wu, “Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-hour and After-hours Revisions,” *Journal of Accounting Research*, 2015.

**Table 1: Fixed Effects
Post-Relevant Halfhours Versus Control Halfhours
(2014 - September 2021)**

Control Variable	Fixed Effect	Estimate	
		Based on Key Developments Abnormal Returns	Based on Earnings Announcements Abnormal Returns
Ticker	Intercept	44.756% *** (1,021.073)	44.818% *** (1,004.707)
	Post-Relevant HalfHours	0.006% *** (1.160)	-0.272% *** (-69.235)
Ticker * Year	Intercept	44.791% *** (371.198)	44.864% *** (376.214)
	Post-Relevant HalfHours	-0.013% *** (-2.654)	-0.301% *** (-80.512)
Ticker * Half-Year	Intercept	44.584 *** (249.479)	44.688% *** (270.393)
	Post-Relevant HalfHours	-0.013% *** (-2.607)	-0.313% *** (-85.104)
Ticker * Quarter	Intercept	44.726% *** (181.610)	44.826% *** (189.107)
	Post-Relevant HalfHours	-0.011% ** (-2.378)	-0.333% *** (-91.710)
Ticker * Month	Intercept	44.537% *** (114.610)	44.721% *** (113.223)
	Post-Relevant HalfHours	-0.038% *** (-7.988)	-0.399% *** (-109.804)
Ticker and Year	Intercept	44.623% *** (1,019.048)	44.687% *** (1,002.605)
	Post-Relevant HalfHours	-0.016% *** (-3.036)	-0.320% *** (-81.579)
Ticker and Half-Year	Intercept	45.184% *** (1,031.151)	45.242% *** (1,014.331)
	Post-Relevant HalfHours	-0.018% *** (-3.458)	-0.333% *** (-84.956)
Ticker and Quarter	Intercept	46.555% *** (1,059.023)	46.627% *** (1,041.791)
	Post-Relevant HalfHours	-0.012% ** (-2.352)	-0.349% *** (-89.224)
Ticker and Month	Intercept	46.867% *** (1,052.597)	46.957% *** (1,034.992)
	Post-Relevant HalfHours	-0.003% *** (-0.489)	-0.372% *** (-95.395)

t-statistics are reported in parentheses. ***, ** and * denote two-tailed statistical significance at 1%, 5% and 10% levels.
Economically significant positive impacts are highlighted in green and economically significant negative impacts are highlighted in red.

6.3 Objective, Systematic, and Ordinal *Per Se* Measures of Market Efficiency

As described in Subsections 4.3 and 4.4, for each stock i , for each potentially material event at halfhour T , we consider the announcement window halfhours to be $\tau \in \{T, \dots, T + 2 - 1\} = \{T, T + 1\}$ ($n = 2$ halfhours), the relevant window halfhours to be $\tau \in \{T + 1 + 1, \dots, T + 2 + 2 - 1\} = \{T + 2, T + 3\}$ ($m = 2$ halfhours), and the control halfhours are all the halfhours that are neither announcement window halfhours nor relevant window halfhours.⁷¹ We calculate the absolute abnormal return $\left| \widehat{AbNEqRet}_{i,\tau} \right|$, for each stock i , for each halfhour τ . A systematic and controlled contrast between $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for relevant window halfhours versus control (non-announcement and non-relevant) window halfhours — measured by the negative of the coefficient of the fixed effect of the interaction between the indicator variable, and as the case maybe, ticker and/or time period of interest in the regression of halfhour-level absolute abnormal returns on tickers, time periods, and interactions — provides an objective, systematic and ordinal actual *per se* measure of market efficiency for the relevant ticker, time period, or ticker-time period.

Systematic, independent, and objective characterizations of each ticker-year, ticker-halfyear, ticker-quarter, and ticker-month, and each year, halfyear, quarter, and month, 2014 - September 2021, as statistically and economically significant efficient, statistically and economically significant inefficient, or otherwise, are available upon request from the corresponding author.

⁷¹Please see Rajeev Bhattacharya and Mahendra Gupta, “Impact of FINRA,” *SSRN*, 2023, for different sensitivities.

7 Conclusions

Analyzing all publicly traded U.S. stocks for 2014 - September 2021, using intraday data from TAQ, TRACE, I/B/E/S, and Capital IQ, using daily data from CRSP, Compustat, CRSP-Compustat Merged Database, and FRED, we found that all reaction, overreaction, correction, overcorrection, bounceback, etc., are systemically all out of the system within two hours after a potentially material event for all publicly traded U.S. equities over 2014 - September 2021. Therefore, it is imperative to use high-frequency intraday data for event studies and market efficiency work: 1) systemically, two hours are sufficient to measure the impact of a potentially material event in question, and 2) if one were to use daily data, one would miss the impact of an event that reverts quickly, and/or worse yet, one could erroneously attribute the impact of entirely unrelated events to the potentially material event in question. Thus, all previous event studies and market efficiency work using daily data, while of ground-breaking significance in the past, have only historical value now.

References

Altınkılıç, O., and Hansen, R. S., 2009, “On the Information Role of Stock Recommendation Revisions,” *Journal of Accounting and Economics*, 48, 17-36.

Aman, H., Berkman, H., Smith, T., et. al., 2019, “Responsible Science: Celebrating the 50-year Legacy of Ball and Brown (1968) Using a Registration-Based Framework,” *Pacific-Basin Finance Journal*, 56, 129-150.

Ball, R., 2017, “Fama, Fisher, Jensen, and Roll (1969) — Retrospective Comments,” In: Cochrane, J., Moskowitz, T. (Eds.), *The Fama Portfolio*, Chicago, IL:

University of Chicago Press.

Ball, R., and Brown, P., 1968, “An Empirical Evaluation of Accounting Income Numbers,” *Journal of Accounting Research*, 6(2), 159-178.

Barclay, M., and Litzenberger, R., 1988, “Announcement effects of new equity issues and the use of intraday price data,” *Journal of Financial Economics*, 21, 71–99.

Bhattacharya, R., 2023, *Uncertainty and Risk, Theory and Empirics: With Applications to Big Data in Finance*, London, UK: World Scientific (forthcoming)

Bhattacharya, R., 2019, “Objective Measures of Market Efficiency; Applications to Securities Class Actions and Valuations,” *Berkeley Business Law Journal*, 2019, 249-266.

Bhattacharya, R., 2019-b, “An Option Theoretic Approach to Market Efficiency,” *Annals of Financial Economics*, 14(4), 1-21.

Bhattacharya, R., and Gupta, M., 2023, “Diligence, Objectivity, Quality, and Accuracy,” *Journal of Accounting Literature* (forthcoming).

Bhattacharya, R., and Gupta, M., 2023-b, “Impact of FINRA 2241,” *SSRN*.

Bhattacharya, R., and O’Brien, S., 2015, “Arbitrage Risk and Market Efficiency — Applications to Securities Class Actions,” *Santa Clara Law Review*, 55, 643-672.

Boehmer, E., and Kelley, E., 2009, “Institutional Investors and the Informational Efficiency of Prices,” *Review of Financial Studies*, 22(9), 3563-3594.

Boehmer, E., Jones, C., and Zhang, X., 2019, “Potential pilot problems: Treatment spillovers in financial regulatory experiments,” *Journal of Financial Economics*, 135(1), 68-87

Boehmer, E., and Wu, J., 2013, “Short Selling and the Price Discovery Process,”

Review of Financial Studies, 26(2), 287-322.

Bris, A., Goetzmann, W., and Zhu, N., 2007, "Efficiency and the Bear: Short Sales and Markets Around the World," *Journal of Finance*, 62 (3), 1029-1079.

Brown, S., and Warner, J., 1985, "Using daily stock returns: The case of event studies," *Journal of Financial Economics*, 14(1), 3-31.

Busse, J., and Green, T.C., 2002, "Market efficiency in real time," *Journal of Financial Economics*, 65(3), 415-437.

Budish, E., Cramton, P., and Shim, J., 2015, "The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response," *Quarterly Journal of Economics*, 130(4), 1547-1621.

Campbell, J., Lo, A., MacKinlay, A.C., 1997, *The Econometrics of Financial Markets*, Princeton, NJ: Princeton University Press.

Cao, C., Liang, B., Lo, A., and Petrasek, L., 2018, "Hedge Fund Holdings and Stock Market Efficiency," *Review of Asset Pricing Studies*, 8(1), 77-116.

Chiang, C., Dai, W., Fan, J., Hong, H., and Tu, J., 2016, "Robust Measures of Earnings Surprises," *SSRN*.

Chordia, T., Roll, R., and Subrahmanyam, A., 2005, "Evidence on the speed of convergence to market efficiency," *Journal of Financial Economics*, 76(2), 271-292.

Cornell, B., and Rutten, J., 2006, "Market Efficiency, Crashes, and Securities Litigation," *Tulane Law Review*, 81(2), 443-472.

Collins, D., and Kothari, S.P., 1989, "An analysis of intertemporal and cross-sectional determinants of earnings response coefficients," *Journal of Accounting and Economics*, 11(2-3), 143-181.

Dann, L., Mayers, D., and Raab, R., 1977, “Trading rules, large blocks and the speed of adjustment,” *Journal of Financial Economics*, 4, 3–22.

Fama, E., 1970. “Efficient Capital Markets: A Review of Theory and Empirical Work,” *Journal of Finance*, 25(2), 383-417.

Fama, E., and French, K., 2015, “A five-factor asset pricing model,” *Journal of Financial Economics*, 116, 1–22.

Fama, E., and French, K., 1993, “Common risk factors in the returns on stocks and bonds,” *Journal of Financial Economics*, 33(1), 3-56.

Fama, E., and French, K., 1992, “The Cross-Section of Expected Stock Returns,” *Journal of Finance*, 47(2), 427-465.

Fama, E., Fisher, L., Jensen, M., and Roll, R., 1969, “The Adjustment of Stock Prices to New Information,” *International Economic Review*, 10(1), 1-21.

Foster, F., and Viswanathan, S., 1996, “Strategic Trading When Agents Forecast the Forecasts of Others,” *Journal of Finance*, 51(4), 1437-1478.

Graham, J.R., Koski, J., and Loewenstein, U., 2006, “Information flow and liquidity around anticipated and unanticipated dividend announcements,” *Journal of Business*, 79, 2301–2336.

Greene, W., 2018, *Econometric Analysis*, Upper Saddle River, NJ: Pearson.

Grégoire, V., and Martineau, C., 2022, “How Is Earnings News Transmitted to Stock Prices?,” *Journal of Accounting Research*, 60(1), 261-297.

Grossman, S., and Stiglitz, J., 1980, “On the Impossibility of Informationally Efficient Markets,” *American Economic Review*, 70(3), 393-408.

Harris, L., 2003, *Trading & Exchanges: Market Microstructure for Practitioners*,

New York, NY: Oxford University Press.

Hou, K., and Moskowitz, T., 2005, "Market Frictions, Price Delay, and the Cross-Section of Expected Returns," *Review of Financial Studies*, 18(3), 981-1020.

Jennings, R., and Starks, L., 1986, "Earnings Announcements, Stock Price Adjustment, and the Existence of Option Markets," *Journal of Finance*, 41(1), 107-125.

Jensen, M., 1978, "Some anomalous evidence regarding market efficiency," *Journal of Financial Economics*, 6(2-3), 95-101.

Jiang, C., Likitapiwat, T., and McInish, T., 2012, "Information Content of Earnings Announcements: Evidence From After-Hours Trading," *Journal of Financial and Quantitative Analysis*, 47(6), 1303-1330.

Kaourma, F., Milidonis, A., Nishiotis, G.P., and Panayides, M.A., 2021, "News and Intraday Retail Investor Order Flow in Foreign Exchange Markets," *SSRN*.

Keown, A., and Pinkerton, J., 1981, "Merger Announcements and Insider Trading Activity: An Empirical Investigation," *Journal of Finance*, 36(4), 855-869.

Kim, S., Lin, J., and Slovin, M., 1997, "Market structure, informed trading, and analysts' recommendations," *Journal of Financial and Quantitative Analysis*, 32, 507-524

Kothari, S.P., 2001, "Capital markets research in accounting," *Journal of Accounting and Economics*, 31(1-3), 105-231.

Kothari, S.P., So, E., and Verdi, R., 2016, "Analysts' Forecasts and Asset Pricing: A Survey," *Annual Review of Financial Economics*, 8, 197-219.

Kothari, S.P., and Warner, J., 2007, "Econometrics of Event Studies," In: Eckbo, E. (Ed.), *Handbook of Empirical Corporate Finance*, Amsterdam, The Netherlands:

Elsevier/North-Holland.

Kyle, A., and Obizhaeva, A., 2016, “Market Microstructure Invariance: Empirical Hypotheses,” *Econometrica*, 84(4), 1345-1404.

Li, E. X., Ramesh, K., Shen, M., and Wu, J.S, 2015, “Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-hour and After-hours Revisions,” *Journal of Accounting Research*, 53, 821–61.

Lloyd Davies, P., and Canes, M., 1978, “Stock prices and the publication of second-hand information,” *Journal of Business*, 51, 43–56.

Loughran, T., and Ritter, J., 2000, “Uniformly least powerful tests of market efficiency,” *Journal of Financial Economics*, 55(3), 361-389.

Malkiel, B., 1992, “Efficient market hypothesis,” In: Newman, P., Milgate, M., and Eatwell, J. (Eds.), *New Palgrave Dictionary of Money and Finance*, London, UK: Macmillan.

Marshall, B., Nguyen, N., and Visaltanachoti, N., 2019, “A Note on Intraday Event Studies,” *European Accounting Review*, 28(3), 605-619.

Martineau, C., 2022, “Rest in Peace Post-Earnings Announcement Drift,” *Critical Finance Review*, 11(3-4), 613-646.

Matsumoto, D., Pronk, M., and Roelofsen, E., 2011, “What Makes Conference Calls Useful? The Information Content of Managers’ Presentations and Analysts’ Discussion Sessions,” *The Accounting Review*, 86, 1383–414.

O’Hara, M., 1997, *Market Microstructure Theory*, Malden, MA: Blackwell Publishing.

Patell, J., and Wolfson, M., 1984, “The intraday speed of adjustment of stock

prices to earnings and dividend announcements,” *Journal of Financial Economics*, 13, 223–252.

Porta, R., Lakonishok, J., Shleifer, A., and Vishny, R., 1995, “Good News for Value Stocks: Further Evidence on Market Efficiency,” Working paper, NBER.

Roberts, M., and Whited, T., 2011, “Endogeneity in Empirical Corporate Finance,” In: Constantinides, M., and Stulz, R. (Eds.), *Handbook of the Economics of Finance*, Amsterdam, The Netherlands: Elsevier.

Rogers, J. L., Skinner, D. J., and Zechman, S. L., 2017, “Run EDGAR Run: SEC Dissemination in a High-Frequency World,” *Journal of Accounting Research*, 55, 459–505.

Rogers, J. L., Skinner, D. J., and Zechman, S. L., 2016, “The Role of the Media in Disseminating Insider-Trading News,” *Review of Accounting Studies*, 21, 711-39.

Rosch, D., Subrahmanyam, A., and Dijk, M., 2017, “The Dynamics of Market Efficiency,” *Review of Financial Studies*, 30(4), 1151–1187.

Saffi, P., and Sigurdsson, K., 2011, “Price Efficiency and Short Selling,” *Review of Financial Studies*, 24(3), 821-852.

Saggu, A., 2022, “The intraday bitcoin response to tether minting and burning events: Asymmetry, investor sentiment, and ‘whale alerts’ on Twitter,” *Finance Research Letters*, 49, 103096.

Samuelson, P., 2009, “An Enjoyable Life Puzzling Over Modern Finance Theory,” *Annual Review of Financial Economics*, 1, 19-35.

Shleifer, A., 2000, *Inefficient Markets — An Introduction to Behavioral Finance*, New York, NY: Oxford University Press.

Stambaugh, R., Yu, J., and Yuan, Y., 2015, “Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle,” *Journal of Finance*, 70(5), 1903-1948.

Wooldridge, J., 2010, *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press.

Data

[dataset] CapitalIQ

[dataset] Compustat

[dataset] Compustat-CRSP Merged Database

[dataset] CRSP

[dataset] Federal Reserve of St. Louis

[dataset] I/B/E/S

[dataset] TAQ

[dataset] TRACE

TECHNICAL APPENDIX

A. HalfHour-Level Averages

Table Appendix-1								
Comparison of Intraday Data and Daily Data (2014 - September 2021)								
Year	Quarter	Intraday Data				Daily Data		
		Number of Equity Trades	Dollar Value of Equity Trades	Number of Fixed Income Trades	Dollar Value of Fixed Income Trades	Number of Observations	Number of Equity Trades	Dollar Value of Equity Trades
2014	1	1,926,239,343	\$17,325,394,026,361	4,020,360	\$3,175,662,358,003	406,135	610,688,409	\$16,561,835,009,089
2014	2	1,819,263,091	\$16,870,778,971,035	3,894,265	\$3,345,962,083,196	423,927	608,695,640	\$15,101,700,758,067
2014	3	1,707,216,092	\$15,653,454,170,425	3,598,767	\$2,814,186,446,991	436,861	551,627,996	\$14,784,073,442,796
2014	4	2,130,705,576	\$18,881,074,072,187	3,717,768	\$2,761,439,273,092	439,750	620,399,242	\$18,072,918,510,342
2015	1	1,962,515,129	\$17,945,195,452,977	4,051,157	\$3,515,582,919,475	419,932	573,169,320	\$17,159,703,006,802
2015	2	1,819,257,164	\$16,923,993,048,630	3,933,485	\$3,217,949,348,199	435,121	571,228,779	\$16,149,517,762,112
2015	3	2,246,183,807	\$19,442,171,278,550	3,764,267	\$2,846,661,200,411	446,279	682,920,742	\$18,473,574,210,343
2015	4	2,190,577,282	\$18,038,112,447,226	4,041,987	\$2,491,898,904,323	445,217	650,250,048	\$17,221,476,055,313
2016	1	2,573,524,217	\$19,557,899,479,956	4,797,632	\$3,167,909,880,109	422,681	719,933,406	\$18,330,922,510,727
2016	2	2,182,293,644	\$17,648,220,098,305	4,840,824	\$2,983,717,736,637	442,125	634,565,530	\$16,572,525,778,322
2016	3	1,960,121,791	\$16,497,805,893,703	4,741,883	\$3,399,978,725,728	441,043	581,883,805	\$15,661,244,171,624
2016	4	2,095,576,792	\$18,451,657,041,161	4,642,104	\$2,840,805,528,573	434,923	611,300,335	\$16,983,988,660,102
2017	1	1,985,023,203	\$18,330,144,176,777	5,547,976	\$3,808,230,612,062	430,830	599,386,840	\$16,484,927,265,961
2017	2	1,996,798,376	\$19,096,466,633,198	5,080,229	\$2,807,783,242,248	438,367	636,673,058	\$17,100,088,311,885
2017	3	1,834,993,857	\$17,942,809,260,986	4,837,590	\$2,983,970,309,925	439,735	609,004,162	\$16,005,584,543,889
2017	4	1,927,015,182	\$19,563,715,121,913	5,071,931	\$3,465,996,879,419	443,069	655,140,250	\$17,459,055,144,045
2018	1	2,304,180,434	\$25,586,514,195,804	5,815,831	\$3,655,777,849,862	433,696	754,355,501	\$22,988,132,556,037
2018	2	2,177,514,051	\$23,416,749,216,858	5,753,988	\$3,370,717,409,037	454,271	736,971,155	\$20,957,921,093,798
2018	3	2,013,157,733	\$21,536,136,794,314	5,495,425	\$3,727,590,043,464	450,465	712,470,057	\$19,337,285,812,799
2018	4	2,701,465,727	\$28,112,617,971,647	5,934,010	\$3,212,327,539,018	457,096	898,983,275	\$25,364,396,813,419
2019	1	2,212,168,304	\$23,111,156,936,584	6,503,878	\$3,605,987,852,834	444,984	763,001,652	\$20,669,373,385,765
2019	2	2,271,740,093	\$22,578,787,230,748	6,044,307	\$3,336,416,204,852	461,168	796,301,541	\$20,206,977,932,884
2019	3	2,416,943,077	\$23,517,503,011,696	5,903,773	\$3,104,341,630,452	471,874	822,578,085	\$20,005,572,861,668
2019	4	2,324,607,671	\$24,426,647,056,441	5,749,135	\$2,804,876,287,796	473,664	813,980,031	\$19,332,691,236,845
2020	1	3,677,867,162	\$36,816,084,177,934	6,617,358	\$4,513,126,813,699	461,706	1,278,523,131	\$30,981,985,774,839
2020	2	4,003,414,165	\$34,717,522,262,877	6,536,712	\$4,300,699,316,331	468,303	1,465,416,736	\$29,508,606,104,973
2020	3	3,531,389,334	\$34,721,783,580,982	5,470,990	\$3,276,410,577,952	481,823	1,517,808,342	\$29,223,224,882,992
2020	4	3,650,186,844	\$36,971,749,242,935	5,424,712	\$2,950,194,339,277	493,679	1,561,035,312	\$30,510,486,861,305
2021	1	4,303,573,977	\$40,573,491,653,630	6,378,585	\$4,012,258,125,333	490,660	2,203,796,372	\$37,891,833,934,853
2021	2	3,247,963,604	\$32,508,643,000,085	5,943,040	\$3,600,868,839,454	527,913	1,800,262,049	\$33,347,651,060,651
2021	3	3,978,095,420	\$39,199,715,706,215	5,323,463	\$2,995,045,350,079	554,454	1,756,773,810	\$32,523,026,167,471

Table Appendix-2
Halfhour-Level Summary Statistics (2014 - September 2021)

Halfhour	Description	Number of Equity Trades	Dollar Value of Equity Trades	Number of Fixed Income Trades	Dollar Value of Fixed Income Trades
0	Before 9:30 AM U.S. Eastern	640,483,038	\$6,777,863,422,227	11,305,416	\$11,206,970,976,201
1	9:30 AM - 10 AM U.S. Eastern	8,765,560,268	\$88,342,871,897,940	6,734,369	\$4,372,031,645,262
2	10 AM - 10:30 AM U.S. Eastern	7,186,315,118	\$57,282,665,647,677	8,691,571	\$4,860,415,458,364
3	10:30 AM - 11 AM U.S. Eastern	6,289,105,358	\$48,329,343,516,871	9,759,649	\$5,614,909,986,256
4	11 AM - 11:30 AM U.S. Eastern	5,706,463,977	\$43,620,109,464,877	10,553,069	\$5,794,441,646,635
5	11:30 AM - 12 PM U.S. Eastern	5,049,692,932	\$38,297,562,040,105	10,058,513	\$5,099,021,334,234
6	12 PM - 12:30 PM U.S. Eastern	4,534,691,961	\$33,924,575,217,106	9,866,459	\$5,107,833,767,588
7	12:30 PM - 1 PM U.S. Eastern	4,278,316,329	\$31,571,903,696,950	8,850,021	\$4,336,087,866,003
8	1 PM - 1:30 PM U.S. Eastern	4,160,932,285	\$31,092,087,818,446	8,883,699	\$4,498,974,933,412
9	1:30 PM - 2 PM U.S. Eastern	4,278,402,702	\$31,160,890,672,212	11,018,262	\$5,783,461,072,224
10	2 PM - 2:30 PM U.S. Eastern	4,792,257,411	\$35,486,737,961,208	9,883,277	\$5,392,447,019,295
11	2:30 PM - 3 PM U.S. Eastern	5,010,038,857	\$36,504,042,353,304	10,307,489	\$5,775,356,612,305
12	3 PM - 3:30 PM U.S. Eastern	6,106,685,431	\$43,987,366,210,054	12,052,614	\$7,383,178,562,403
13	3:30 PM - 4 PM U.S. Eastern	14,313,900,845	\$103,332,011,862,963	16,454,641	\$9,619,493,708,915
14	After 4 PM U.S. Eastern	490,529,064	\$151,474,382,823,856	15,058,383	\$17,249,749,038,735

We use intraday equity trading data from TAQ and intraday fixed income security trading data from TRACE. We divide each trading day into 15 halfhours as follows: halfhour 0 for prior to 9:30 AM, halfhour 14 for after 4 PM, and halfhours 1-13 for each half-hour of the trading hours. For each stock i , for each trading day, for each halfhour $\tau = \{0, 1, \dots, 14\}$ with positive volume, we calculate the Volume-Weighted Average Price

$$VWAP_{i,\tau} = \frac{\sum_{l \in \tau} (Trading_Price_{i,l}) (Equity_Volume_{i,l})}{\sum_{l \in \tau} (Equity_Volume_{i,l})}$$

of trading prices, and then calculate the relevant continuously compounded return

for halfhour τ

$$EqRet_{i,\tau} = \ln(VWAP_{i,\tau}) - \ln(VWAP_{i,\tau-1})$$

where

$$Equity_Volume_{i,\tau}$$

and

$$Fixed_Income_Volume_{i,\tau}$$

denote the equity volume and fixed income volume for ticker i in halfhour τ .

We calculate the various weighted averages for equity returns as follows.

$$EqRet_AllHalfHour_\tau = \frac{\sum_j (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_j (Equity_Volume_{j,\tau})}$$

$$EqRet_NasdaqHalfHour_{i,\tau} = \frac{\sum_{j \in Nasdaq} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in Nasdaq} (Equity_Volume_{j,\tau})}$$

$$\begin{aligned}
& EqRet_NAICS3DigHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in NAICS-3Digit} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in NAICS-3Digit} (Equity_Volume_{j,\tau})}
\end{aligned}$$

$$\begin{aligned}
& EqRet_MCApDecileHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in Market-Cap-Decile} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in Market-Cap-Decile} (Equity_Volume_{j,\tau})}
\end{aligned}$$

$$\begin{aligned}
& EqRet_IntraVtyDecileHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in IntraDay-Volatility-Decile} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in IntraDay-Volatility-Decile} Equity_Volume_{j,\tau}}
\end{aligned}$$

$$\begin{aligned}
& EqRet_DivYieldDecileHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in Dividend-Yield-Decile} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in Dividend-Yield-Decile} (Equity_Volume_{j,\tau})}
\end{aligned}$$

$$\begin{aligned}
& EqRet_BMRatioDecileHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in \text{Book-to-Market-Ratio-Decile}} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in \text{Book-to-Market-Ratio-Decile}} (Equity_Volume_{j,\tau})}
\end{aligned}$$

$$\begin{aligned}
& EqRet_PERatioDecileHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in \text{Price-to-Earnings-Ratio-Decile}} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in \text{Price-to-Earnings-Ratio-Decile}} (Equity_Volume_{j,\tau})}
\end{aligned}$$

$$\begin{aligned}
& EqRet_DERatioDecileHalfHour_{i,\tau} \\
= & \frac{\sum_{j \in \text{Debt-to-Equity-Ratio-Decile}} (EqRet_TickerHalfHour_{j,\tau}) (Equity_Volume_{j,\tau})}{\sum_{j \in \text{Debt-to-Equity-Ratio-Decile}} (Equity_Volume_{j,\tau})}
\end{aligned}$$

For each fixed income security Ticker-Cusip, we calculate the volume-weighted average yield (VWAY)

$$\begin{aligned}
& VWAY_{i,\tau} = FIYld_Ticker_Cusip_HalfHour_{i,\tau} \\
= & \frac{\sum_{l \in \tau} (Fixed_Income_Yield_{i,l}) (Fixed_Income_Volume_{i,l})}{\sum_{l \in \tau} (Fixed_Income_Volume_{i,l})}
\end{aligned}$$

and for each Ticker, we calculate the simple average of VWAY over all Cusips corresponding to that Ticker. Since we are using yield-to-maturity (YTM) with traded prices for the FI securities, we have comparability across different coupons, maturities, and periodicities, thus, the following average is meaningful, and we use a simple average to avoid the volatility of ticker-halfhour-yield because of substantially differing trading volumes. We am still left with other complexities such as seniority and convertibility, but we do not have these data.

$$\begin{aligned}
 & FIYld_TickerHalfHour_{i,\tau} \\
 &= \frac{\sum_{Cusip \in Ticker} (FIYld_Ticker_Cusip_HalfHour_{i,\tau})}{\sum_{Cusip \in Ticker} (1)}
 \end{aligned}$$

$$\begin{aligned}
 & FIYld_AllHalfHour_{\tau} \\
 &= \frac{\sum_j (FIYld_TickerHalfHour_{j,\tau}) (Fixed_Income_Volume_{j,\tau})}{\sum_j (Fixed_Income_Volume_{j,\tau})}
 \end{aligned}$$

And

$$\begin{aligned}
 & RiskFree_{\tau} \\
 &= \text{Yield of T-Bill, 4-Weeks Maturity, for Date including HalfHour } \tau
 \end{aligned}$$

$$\begin{aligned}
& \text{NomBroadUSDIndex}_\tau \\
& = \text{Nominal Broad US Dollar Index for Date including HalfHour } \tau
\end{aligned}$$

B. Market Model

The market model is given by the return of Ticker i in halfhour τ , $EqRet_{i,\tau}$

$$\begin{aligned}
& = \pi \\
& + (\pi_{EqRet_AllHalfHour}) (EqRet_AllHalfHour_\tau) \\
& + (\pi_{EqRet_Nasdaq_HalfHour}) (EqRet_NasdaqHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_NAICS3DigHalfHour}) (EqRet_NAICS3DigHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_MCapDecileHalfHour}) (EqRet_MCapDecileHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_IntraVtyDecileHalfHour}) (EqRet_IntraVtyDecileHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_DivYieldDecileHalfHour}) (EqRet_DivYieldDecileHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_BMRatioDecileHalfHour}) (EqRet_BMRatioDecileHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_PERatioDecileHalfHour}) (EqRet_PERatioDecileHalfHour_{i,\tau}) \\
& + (\pi_{EqRet_DERatioDecileHalfHour}) (EqRet_DERatioDecileHalfHour_{i,\tau}) \\
& + (\pi_{FIYld_AllHalfHour}) (FIYld_AllHalfHour_\tau) \\
& + (\pi_{RiskFree}) (RiskFree_\tau) \\
& + (\pi_{NomBroadUSDIndex}) (NomBroadUSDIndex_\tau) \\
& + AbNEqRet_{i,\tau}
\end{aligned}$$

Table Appendix-3
Summary Statistics of Market Model Variables (2014 - September 2021)

Regressor	Number of Obs	Mean	Standard Deviation	Upper Quartile	Median	Lower Quartile
EqRet_TickerHalfHour	50,106,402	-0.0000010	0.0886823	0.0025405	0.0000000	-0.0025618
EqRet_AllHalfHour	28,978	0.0019833	0.0280379	0.0026144	0.0002849	-0.0019915
EqRet_NasdaqHalfHour	57,956	0.0016141	0.0304606	0.0026501	0.0002452	-0.0021699
EqRet_NAICS3DigHalfHour	2,312,853	-0.0001584	0.0397222	0.0021762	0.0000352	-0.0020869
EqRet_MCapDecileHalfHour	289,753	0.0008127	0.0401322	0.0034137	0.0001037	-0.0032963
EqRet_IntraVtyDecileHalfHour	179,869	-0.0009897	0.0975003	0.0078628	0.0001303	-0.0071964
EqRet_DivYieldDecileHalfHour	231,817	-0.0001597	0.0307727	0.0021047	0.0001144	-0.0018948
EqRet_BMRatioDecileHalfHour	238,459	0.0005654	0.0408437	0.0030663	0.0001485	-0.0028001
EqRet_PERatioDecileHalfHour	289,724	0.0006007	0.0325037	0.0024571	0.0001316	-0.0022033
EqRet_DERatioDecileHalfHour	281,367	0.0002127	0.0336754	0.0028886	0.0000606	-0.0027801
NomBroadUSDIndex	1,899	110.92702	6.97292	115.31330	112.65630	109.04920
TBill_4Wk	1,919	0.0070353	0.0082358	0.0150000	0.0023000	0.0004000
FIYld_AllHalfHour	28,929	0.0385361	0.0168060	0.0425658	0.0371158	0.0318501

C. Controlled Contrasts

Fix universe of analysis \mathfrak{T} as set of halfhours. Fix announcement window length $n \geq 1$, relevant window length $m \geq 1$, and post-relevant window length $l \geq 1$. Consider a fixed time period t (e.g., quarter, month) as set of halfhours. Consider event identification method $\mathfrak{J} \subseteq \mathfrak{T}$ as potentially material events; in this paper, we use two

identification methods for potentially material events: a) key developments (KD), identified by S&P Global CapitalIQ, and b) earnings announcements and revisions, and analyst forecasts and revisions (EA); see Subsection 4.4 for details. For potentially material event at halfhour $T \in t \cap \mathfrak{T}$, **AnnouncementHalfHours** $(T, n) = \{T, \dots, T + n - 1\}$ (n halfhours), **RelevantHalfHours** $(T, n, m) = \{T + n, \dots, T + n + m - 1\}$ (m halfhours), and, therefore, **TreatmentHalfHours** $(T, n, m) = \mathbf{AnnouncementHalfHours}(T, n) \cup \mathbf{RelevantHalfHours}(T, n, m) = \{T, \dots, T + n + m - 1\}$ ($n+m$ halfhours), and therefore, **ControlHalfHours** (t, n, m, \mathfrak{T}) consists of each halfhour in t that is not a treatment halfhour for any potentially material event at halfhour $T \in t \cap \mathfrak{T}$, and, therefore, equals $\{\tau \in t : \tau \notin \{T, \dots, T + n + m - 1\}, \forall T \in t \cap \mathfrak{T}\}$. And, finally, the list of post-relevant halfhours for event at time halfhour $T \in t$ is **PostRelevantHalfHours** $(T, n, m, l) = \{T + n + m, \dots, T + n + m + l - 1\}$ (l halfhours immediately following the relevant halfhours).

For fixed n, m, l , a systematic and controlled comparison between $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for **PostRelevantHalfHours** (T, n, m, l) versus $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for **ControlHalfHours** (t, n, m, \mathfrak{T}) is a measure of whether there is any systemic impact of the potentially material event T beyond the announcement and relevant halfhours.⁷² If this contrast is not statistically and economically significant positive, it would demonstrate that 1) $(n + m)$ halfhours are systemically sufficient to measure the im-

⁷²The rational expectations models tell us that the speed of impact probably depends on whether there is further information that has not been disclosed; please see F. Douglas Foster and S. Viswanathan, "Strategic Trading When Agents Forecast the Forecasts of Others," *Journal of Finance*, 1996, and Maureen O'Hara, *Market Microstructure Theory*, Malden, MA: Blackwell Publishing, 1997, for example.

fact over l halfhours of a potentially material event in question, and 2) if one were to use daily data, one would miss the impact of an event that reverts quickly, and/or worse yet, one could erroneously attribute the impact of entirely unrelated events to the potentially material event in question, and, therefore, although of enormous historical significance, events studies using daily data would be entirely unreliable today.

For fixed n, m , a systematic and controlled contrast between $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for **RelevantHalfHours** (T, n, m) versus $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ for **ControlHalfHours** (t, n, m, \mathfrak{T}) would be necessary for an objective, systematic and ordinal direct measure of market efficiency with n announcement halfhours and m relevant halfhours. From the theory, it follows that $\left| \widehat{AbNEqRet}_{i,\tau} \right|$ should be weakly higher for relevant halfhours than for control halfhours, and therefore, in this paper, for each of the identification systems for potentially material events (KD and EA), for each n, m , for each security i , for each quarter t , we provide an ordinal direct **measure of market efficiency** for that security for that quarter as the negative of the coefficient of the interaction between the indicator variable for relevant halfhours versus control halfhours, and as the case maybe, ticker and/or time period of interest, in a fixed effects regression of halfhour-level absolute abnormal returns on tickers, time periods, and interactions.⁷³

⁷³In Rajeev Bhattacharya, “Market Efficiency: A Structural Study with Intraday Data,” *SSRN*, 2023, an objective, systematic and ordinal direct measure of market efficiency is provided by the negative of the positive part of the difference in quarterly means between absolute abnormal returns for relevant halfhours and absolute abnormal returns for control halfhours.