Impact of Self-Regulation on Quality of Financial Markets*

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Abstract

The Financial Industry Regulatory Authority (FINRA) 2241 Rules were a major attempt by a self-regulatory organization to improve quality of financial markets. We find that FINRA 2241's impact on each of ten systematic

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and objective market quality metrics was insignificant. We systematically and independently use diligence (probability of analyst's reliance on non-public information), objectivity (probability that an analyst's forecast equals its best estimate), quality (exponent of negative of standard deviation of residuals of the analyst forecast regression equation), and the analyst's *ex post* normalized accuracy. We use four measures of market efficiency for each stock and each quarter, given by controlled contrasts of halfhour-level absolute abnormal returns to a potentially material event in relevant halfhours following an announcement window containing the event versus absolute abnormal returns in control halfhours (halfhours that are not announcement or relevant halfhours corresponding to any potentially material event in that quarter), where potentially material events are separately identified as a) "key developments" (marked by S&P Global CapitalIQ, event types include earnings, dividends, mergers & acquisitions, buybacks, public offerings, management changes, debt defaults, dividend cancellations, and regulatory agency inquiries, sourced from regulatory filings and news vendors), and b) earnings announcements and revisions, and analyst forecasts and revisions.

Keywords. FINRA 2241; Asymmetric Information; Earnings; Management Guidance; Analyst Forecasts; Diligence; Objectivity; Quality; Accuracy; Hausman Specification Test; Wald Test; Bayesian; Market Efficiency; Key Developments; Earnings Announcements; Big Data in Finance.

JEL Codes. K22; M41; G12; G14; G24; C23; C26.

1 Introduction

The objective of the U.S. FINRA (Financial Industry Regulatory Authority),[1] which is an S.R.O. (self-regulatory organization), is "protecting investors and safeguarding market integrity in a manner that facilitates vibrant capital markets."[2] The FINRA 2241 Rules (effective September 25, 2015, and December 24, 2015) were a major attempt by an S.R.O. to improve market quality and required that "a member's written policies and procedures [regarding analyst reports and forecasts] must be reasonably designed to promote objective and reliable research that reflects the truly held opinions of research analysts and to prevent the use of research reports or research analysts to manipulate or condition the market or favor the interests of the member or a current or prospective customer or class of customers. ... A member must establish, maintain and enforce written policies and procedures reasonably designed to ensure that: A) purported facts in its research reports are based on reliable information; and B) any recommendation, rating or price target has a reasonable basis and is accompanied by a clear explanation of any valuation method used and a fair presentation of the risks that may impede achievement of the recommendation, rating or price target."[3]

In this paper, we find that FINRA 2241's impact on *each* of ten objective and systematic market quality metrics — indices of diligence, objectivity, quality, and accuracy by analysts and analyst firms based on Bhattacharya and Gupta (2023)

[1] https://www.finra.org/about.

[2] https://www.finra.org/about#:~:text=FINRA%20is%20dedicated%20to%20protecting,that%20facilitates%20vibrant%20capital%20markets.

[3] https://www.finra.org/rules-guidance/rulebooks/finra-rules/2241?rbid=2403&element_id=11946.

and six measures of market efficiency based on Bhattacharya (2024-c) — was actually *insignificant*.[4]

As in Bhattacharya and Gupta (2023), in order to make our models comparable across firms and industries, and across time, we use multiplicative models in this paper, and in order to implement the multiplicative models that make these comparisons possible, we restrict ourselves to positive earnings, management guidance, and analyst forecasts.[5] We rely upon Bhattacharya (2024-a), as follows: By normalizing each variable (except for an indicator or time variable) by the Gaussian cumulative probability of its Z-score[6] — this is a rigorization of the number of standard deviations approach to interpretation of coefficients, which also implicitly assumes Gaussian distributions — we make the associations of variables comparable, thereby allowing a systematic and objective definition of actual significance, which is different from statistical significance.[7]

The paper is organized as follows. Section 2 reviews the literature and develops the research hypothesis of this paper. Section 3 describes the data and econometrics of this paper. Section 4 details the impact of FINRA 2241 on each of these four analyst behavior indices and the six measures of market efficiency. Section 5 concludes and discusses future research. The Technical Appendix contains the details of the econometric methodology and the structural system.

[4] We have repeatedly engaged with the team of economists at FINRA to address these issues, but have not received a meaningful response. Please see Johnson and Cureton (2021), for instance, on Immanuel Kant's opinion on self-regulation being a contradiction in terms; therefore, the failure of an S.R.O. such as FINRA is not surprising, we thank Philip Evans for the insight.

[5] Please see the differences between Tables 1 and 1 B for details on the impact of these positivity filters.

[6] $Z\text{-}Score\,(x) = (x \text{ } minus \text{ } Mean\,(x))\,/\,(Standard\ Deviation\,(x))$.

[7] Pretty much everything is statistically significant when working with huge datasets.

2 Literature Review and Hypothesis Development

The impact on capital markets of regulatory and other organizations such as the U.S. Securities and Exchange Commission (SEC) and FINRA have been studied in the accounting and finance literature. Call, Sharp and Wong (2019) "find that after a sanction, analysts at sanctioned brokerages lower their stock recommendations, both in absolute terms and relative to the recommendations of other analysts following the same firms. These analysts are also more likely than analysts at other brokerages to downgrade a company's stock after the receipt of unfavorable information about the firm." Clarke, Khorana, Patel and Rau (2011) "examine the impact of NASD Rule 2711, NYSE Rule 472, and the Global Research Settlement on the recommendation performance of independent, affiliated, and unaffiliated analysts ... find that analysts from all three types of institutions issued fewer strong buys following these regulations designed to separate investment banking and equity research ... affiliated analysts were less likely to issue innovative recommendations." Barniv, Hope, Myring and Thomas (2009) "find that the negative relation between analysts' stock recommendations and residual income valuations is diminishing following regulations." Chen and Chen (2009) study "changes in how analysts generate stock recommendations after the SEC's approval of NASD Rule 2711 in May 2002, which introduced regulatory reforms to enhance the independence of analysts' research ... find a stronger relation between analysts' stock recommendations and [analysts' earnings forecasts relative to the stock prices] and a weaker relation between analysts' stock recommendations and conflicts of interest in the post-Rule period than prior to the implementation of the Rule." Kadan, Madureira, Wang and Zach (2009) "study the effect of the Global Analyst Research Settlement and related regulations on sell-side research ... document that optimistic recommendations have become less frequent and more informative, whereas neutral and pessimistic recommendations have become more frequent and less informative ... the overall informativeness of recommendations has declined." Ertimur, Sunder and Sunder (2007) "find that regulatory reforms aimed at mitigating analyst conflicts of interest appear to have improved the relation between accuracy and profitability ... the integrity of buy and hold recommendations has improved and the change is more pronounced for analysts expected to be most conflicted."[8]

This current paper is anchored in this past research and tests the **research hypothesis** that FINRA 2241 improved market quality, measured by ten separate systematic and objective metrics, the quarterly indices of diligence, objectivity, quality, and accuracy by analysts and analyst firms studied by Bhattacharya and Gupta (2023) and the six separate quarterly ordinal measures of the efficiency of the market for a stock studied by Bhattacharya (2024-c). Bhattacharya and Gupta (2023) provide a general framework of behavior under asymmetric information and systematically and objectively characterize and analyze **diligence** (the probability of reliance on non-public information, the index of diligence equals one minus the p-value of the Hausman Specification Test of Ordinary Least Squares (OLS) versus Two Stage Least Squares (2SLS)), **objectivity** (the probability that an analyst's forecast equals its best estimate, the index of objectivity equals the p-value of the Wald Test of zero coefficients versus non-zero coefficients in the Two Stage Least

[8]Please see also Fisch (2007), and Barber, Lehavy, McNichols and Trueman (2006).

Squares regression of the EPS forecast residuals on public information), **quality** (the exponent of the negative of the standard deviation of residuals of the analyst forecast regression equation provides the index of analytical quality), and the *ex post* **normalized accuracy** (the index of *ex post* normalized accuracy is the exponent of the negative of the absolute difference between the log of analyst forecast and the log of announced EPS, when both are positive) of forecasts provided by analysts and analyst firms. Market efficiency is a very important concept and is well recognized for its importance in guiding many market activities. In particular, if the market for an asset is efficient, the market price of the asset equals its true economic value, which implies that investors can rely[9] upon market prices for value and do not have to spend expensive time and resources (which are essentially only available to institutional investors) to further investigate the value of an asset. In other words, if the market for an asset is not efficient, the market price of the asset is misleading in terms of an investor's decisions. Efficient capital markets, therefore, provide substantial social benefits and are a *sine qua non* for the democratization of markets and the protection of investors, and constitute a critical mission of regulatory bodies such as the U.S. Securities and Exchange Commission (SEC) and the U.S. Financial Regulatory Authority (FINRA). 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.* Bhattacharya (2024-c), provides

[9] "Reliance" on price for value is an important component of class certification in securities class actions; please see Bhattacharya, Bial and Evans (2024) for details.

measures of market efficiency for each stock and each quarter, given by controlled contrasts of halfhour-level absolute abnormal returns to a potentially material event in relevant halfhours following an announcement window containing the event versus absolute abnormal returns in control halfhours (halfhours that are not announcement or relevant halfhours corresponding to any potentially material event in that quarter), where potentially material events are separately identified as a) "key developments" (KD, marked by S&P Global CapitalIQ, event types include earnings, dividends, mergers & acquisitions, buybacks, public offerings, management changes, debt defaults, dividend cancellations, and regulatory agency inquiries, sourced from regulatory filings and news vendors),[10] and b) earnings announcements and revisions, and analyst forecasts and revisions (EA). Bhattacharya (2024-c) calculates the absolute abnormal return $|AbNEqRet_{i,\tau}|$ for each halfhour τ, and for each stock i. A systematic and controlled comparison between $|AbNEqRet_{i,\tau}|$ for relevant halfhours versus control halfhours (non-announcement and non-relevant halfhours) would be necessary for an objective, systematic and ordinal actual measure of market efficiency. From the theory, it follows that $|AbNEqRet_{i,\tau}|$ should be weakly higher for relevant halfhours than for control halfhours, and therefore, for each of KDAR and EAAR, for each announcement window length, for each security i, for each quarter t, the ordinal actual **measure of market efficiency** for that security for that quarter

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

used in this paper is:

$$-\max\left\{0, \begin{array}{c} Mean_{\tau\in\text{Quarter } t,\tau\in\text{Relevant Window}}\left|AbNEqRet_{i,\tau}\right| \\ minus \\ Mean_{\tau\in\text{Quarter } t,\tau\in\text{Control Window}}\left|AbNEqRet_{i,\tau}\right| \end{array}\right\}$$

The data reject the hypothesis that FINRA 2241 improved market quality, detailed in Section 4.

3 Data

We use the time period 2014-September 2018 — please see Law (2021) regarding "anonymization" and "reshuffling" of analyst and analyst firm codes in I/B/E/S data, as a result of which I/B/E/S data beyond October 2018 are unreliable.[11,12] We restrict attention, in CRSP data, to stock-days that have positive closing price, positive shares outstanding, positive daily closing price, non-missing ticker and permno, non-missing daily equity return, non-missing daily equity trading volume, non-missing daily equity closing bid and ask, non-missing exchange membership, and non-missing SIC Code, such that the firm has unique ticker, permno, and major industry sector (two-digit SIC code) over 2014-September 2018. We restrict attention to positive actual EPS, positive management guidance (earnings and guidance data are available from I/B/E/S only for a $StudiedFirm$ in a quarter for which there is analyst cov-

[11] We thank Henk Berkman for pointing this out to us.

[12] The loss of years and firms as a result of these restrictions, *albeit* necessary, is not trivial, please see Tables 1 and 1 B for details.

erage) and positive analyst forecasts (from I/B/E/S) such that the analyst forecast was announced equal to or before the forecast was recorded by I/B/E/S, and such that there are no substantive revisions, as in no changes in the numbers, in earnings, guidance, or forecast.[13]

3.1 Publicly Available Financial Information at Time of Analyst Forecast

We use the following as proxy for the publicly available information (Π_{it}) about the $StudiedFirm$ i (and the market) at quarter t. We recognize that more variables are available to the public, especially non-financial variables,[14] and we urge future research on the robustness of our work on this front. We restrict to these variables for two reasons: a) availability in machine-readable format and b) every additional variable increases by one the number of quarters of data needed to measure diligence and objectivity.

- **Determinants of analyst firm profits and analyst compensation**
  - Mean of daily equity return of the $StudiedFirm$ over the thirty calendar days prior to the analyst forecast
  - Volatility of daily equity return of the $StudiedFirm$ over the thirty calendar days prior to the analyst forecast

[13] We do not have access to a reliable mapping to actual names of analyst firms from the "analys" and "estimator" codes.

[14] Please see, for instance, Ham, Kaplan and Lemayian (2020), for various public variables used in the literature in the context of analyst forecasts.

- Mean of daily market cap of the $StudiedFirm$ over the thirty calendar days prior to the analyst forecast
- Mean of daily trading volume of the $StudiedFirm$ over the thirty calendar days prior to the analyst forecast

- **Analyst history**
  - Latest actual EPS statement known at time of the analyst forecast
  - If the analyst forecast is not the first for the relevant forecast period, we take the moving average of all previous analyst forecasts for that forecast period about the $StudiedFirm$ as an additional piece of publicly available information

- **Market control variable**
  - Mean of daily return of the S&P 500 index over the thirty calendar days prior to the analyst forecast

Table 1

Summary Statistics of Publicly Available Variables, With Positivity Filters

(1996 - September 2018, except 2008-2009)

Variable	Number of Observations	Mean	Standard Deviation	Upper Quartile	Median	Lower Quartile
Log of Analyst Forecast of EPS of Studied Firm	74,141	-0.858	1.037	-0.236	-0.799	-1.427
Log of Management Guidance of EPS of Studied Firm	8,543	-1.166	1.108	-0.478	-1.079	-1.772
Log of Announced EPS	8,720	-1.056	1.053	-0.408	-0.982	-1.635
Log of Ratio of Guidance to Actual of Studied Firm	8,543	-0.110	0.351	-0.024	-0.080	-0.174
Mean of Log of Previous Analyst Forecasts of EPS of Studied Firm in Forecast Period	69,180	-0.816	1.008	-0.220	-0.771	-1.370
Daily Return of Studied Firm, Past Mean	71,536	0.023%	0.567%	0.308%	0.063%	-0.220%
Daily Return of Studied Firm, Past Volatility	71,517	2.125%	1.372%	2.514%	1.761%	1.273%
Log of Difference in Days Between Guidance and Forecast	74,143	0.510	1.879	1.495	-0.216	-0.727
Log of Market Cap of Studied Firm, Past Mean	71,536	22.544	1.755	23.673	22.596	21.342
Log of Trading Volume of Studied Firm, Past Mean	71,536	13.986	1.582	15.036	14.021	12.993
S&P 500 Daily Return, Past Mean	71,536	0.033%	0.225%	0.159%	0.063%	-0.067%

Table 1 B

Summary Statistics of Publicly Available Variables, Without Positivity Filters

(1996 - September 2018, except 2008-2009)

Variable	Number of Observations	Mean	Standard Deviation	Upper Quartile	Median	Lower Quartile
Analyst Forecast of EPS of Studied Firm	117,034	$0.653	$6.664	$0.730	$0.390	$0.170
Management Guidance of EPS of Studied Firm	10,791	$0.464	$2.154	$0.550	$0.273	$0.090
Announced EPS	11,264	$0.482	$1.650	$0.590	$0.300	$0.113
Mean of Previous Analyst Forecasts of EPS of Studied Firm in Forecast Period	108,945	$0.745	$7.970	$0.745	$0.403	$0.190
Daily Return of Studied Firm, Past Mean	111,414	-0.006%	0.643%	0.305%	0.045%	-0.259%
Daily Return of Studied Firm, Past Volatility	111,376	2.221%	1.495%	2.629%	1.815%	1.294%
Log of Difference in Days Between Guidance and Forecast	117,057	1.387	2.276	3.891	0.417	-0.503
Log of Market Cap of Studied Firm, Past Mean	111,414	22.395	1.845	23.657	22.411	21.114
Log of Trading Volume of Studied Firm, Past Mean	111,414	13.942	1.591	15.017	13.978	12.926
S&P 500 Daily Return, Past Mean	111,414	0.035%	0.211%	0.156%	0.060%	-0.070%

Table 2
Correlation Coefficients of All Ordinal Market Quality Metrics
At Year-Quarter Level
(2014-September 2018)

						Quarterly Ordinal Measure of Market Efficiency Based On					
						Key Developments Abnormal Response			Earnings Announcements Abnormal Response		
			Diligence by Analyst -Analyst-Firm	Objectivity by Analyst-Analyst-Firm	Quality of Analysis by Analyst-Analyst-Firm	*Ex Post* Normalized Accuracy by Analyst-Analyst-Firm	60-Minute Announcement Window	90-Minute Announcement Window	120-Minute Announcement Window	60-Minute Announcement Window	90-Minute Announcement Window	120-Minute Announcement Window
		Num of Obs	1,966	1,578	2,182	2,266	1,821	1,821	1,821	1,865	1,865	1,865
Diligence by Analyst-Analyst-Firm			1.000	-0.166	-0.055	0.021	0.031	0.031	0.029	0.036	0.039	0.038
Objectivity by Analyst-Analyst-Firm			-0.166	1.000	0.024	0.067	0.004	-0.007	0.012	-0.018	-0.014	-0.019
Quality of Analysis by Analyst-Analyst-Firm			-0.055	0.024	1.000	0.411	0.092	0.062	0.054	0.160	0.149	0.150
Ex Post Accuracy by Analyst-Analyst-Firm			0.021	0.067	0.411	1.000	0.304	0.275	0.260	0.380	0.369	0.350
Quarterly Ordinal Measure of Market Efficiency Based On	Key Developments Abnormal Response	60-Minute Announcement Window	0.031	0.004	0.092	0.304	1.000	0.947	0.880	0.768	0.758	0.720
		90-Minute Announcement Window	0.031	-0.007	0.062	0.275	0.947	1.000	0.953	0.740	0.736	0.699
		120-Minute Announcement Window	0.029	0.012	0.054	0.260	0.880	0.953	1.000	0.713	0.719	0.696
	Earnings Announcements Abnormal Response	60-Minute Announcement Window	0.036	-0.018	0.160	0.380	0.768	0.740	0.713	1.000	0.979	0.943
		90-Minute Announcement Window	0.039	-0.014	0.149	0.369	0.758	0.736	0.719	0.979	1.000	0.979
		120-Minute Announcement Window	0.038	-0.019	0.150	0.350	0.720	0.699	0.696	0.943	0.979	1.000

4 Impact of FINRA 2241 on Market Quality

In this paper, we investigate the impact of FINRA 2241 on each of ten quarterly market quality metrics, the quarterly indices of diligence, objectivity, quality, and accuracy by analysts and analyst firms based on Bhattacharya and Gupta (2023) and the six separate objective and systematic quarterly ordinal measures of the efficiency of the market for a stock based on Bhattacharya (2024-c).

4.1 Structural System

Based on the market microstructure models in Kyle and Obizhaeva (2016) and Bhattacharya (2019), and in Bhattacharya (2024-c, d), we use an eight-equation structural system and estimate it at the stock-quarter level, where i represents the stock and t represents the quarter.We build on the market microstructure models in Kyle and Obizhaeva (2016) and Bhattacharya (2019) to model equations that have a) each market quality metric as a function of exogenous factors, namely, indicator variable for post-FINRA 2241, dispersion in investor valuations (proxied by the quarterly standard deviation of analyst forecasts of earnings per share for the firm with "forecast period end date" in the current calendar quarter), short sales costs & constraints (proxied by the cost of a synthetic short sale, which is short one call option and long one put option, at the money, with the same expiration), and transaction costs & constraints (proxied by bid-ask spread), and endogenous market activities, namely, Nasdaq listing, Kyle-Obizhaeva liquidity measure,[15] normalized short interest, analyst coverage, institutional ownership of equity, log of market cap, and log of shares outstanding, and b) each endogenous market activity as a function of the exogenous factors and all other endogenous market activities. We use the panel nature of the data to identify appropriate instruments for the endogenous variables and for the variables that are measured with error, and we use Three Stage Least Squares (3SLS) and Errors in Variables (EiV) to estimate this eight-equation structural model and

[15] See Kyle and Obizhaeva (2016).

test our research hypothesis that FINRA 2241 improved market quality.

4.1.1 Notations

- $Metric_{i,t}$ = each separate ordinal market quality metric for stock i in quarter t, described in Section 1
- $FINRA2241_t$ = indicator variable which is zero for quarters prior to Q3-2015 and one for quarters after Q4-2015, and deleting observations for Q3-2015 and Q4-2015
- $Disp_{i,t}$ = dispersion in investor valuations for stock i in quarter t
- $SSCC_{i,t}$ = short sales costs and constraints of stock i in quarter t
- $TrCC_{i,t}$ = transaction costs & constraints of stock i in quarter t
- $Nasdaq_{i,t}$ = indicator variable for Nasdaq listing of firm i (= 1, for a Nasdaq-listed firm, and = 0, otherwise)[16]
- $KOLiq_{i,t}$ = Kyle-Obizhaeva liquidity of stock i in quarter t = cube root [(quarterly mean of halfhour dollar volume)/(square of quarterly standard deviation of halfhour returns)][17]
- $NormSI_{i,t}$ = quarterly mean of (monthly short interest)/(daily shares outstanding) of stock i in quarter t

[16] Whether to list on Nasdaq or on another exchange is a decision, and thus, the Nasdaq listing indicator variable is an endogenous variable.

[17] See Kyle and Obizhaeva (2016).

- $AnCov_{i,t}$ = number of EPS forecasts and revisions by analysts for firm i with "forecast period end date" in quarter t

- $NormInst_{i,t}$ = quarterly mean of institutional ownership percentage in stock i in quarter t

- $logMCap_{i,t}$ = quarterly mean of natural logarithm of daily market cap for stock i in quarter t

- $logShrsOut_{i,t}$ = quarterly mean of natural logarithm of daily shares outstanding for stock i in quarter t

4.1.2 Dispersions of Investor Valuations

The dispersion of investor valuations, which is also a function of the level of uncertainty within the market about the particular firm i in quarter t, is proxied by calculating the quarterly standard deviation of analyst forecasts and analyst forecast revisions of earnings per share (EPS) for firm i,[18] for the firm i with each "forecast period end date" in the current calendar quarter t.

4.1.3 Short Sales Costs & Constraints

We do not have access to actual data on short sales costs & constraints.[19,20] Dealing with missing or unavailable data is one of the biggest challenges in empirical work,

[18] Restricted to forecasts and revisions between $-\$100$ per share and $+\$100$ per share.

[19] We have tried many times, with very influential deans of business schools, as well as C.E.O.s of investment banks, but since the Great Recession, such data have become essentially unavailable to a researcher.

[20] See Ofek, Richardson and Whitelaw (2004) and Cremers and Weinbaum (2010), for instance, on papers that use proprietary data on rebate rates and spreads.

and appropriately proxying for the unavailable data is one of the innovations of this paper. In particular, we use the cost of a synthetic short sale (short one call option and long one put option, at the money, with the same expiration) as a measure of short sales costs & constraints for the underlying stock[21] — please see Evans, Geczy, Musto and Reed (2009), Lamont and Thaler (2003), and Geczy, Musto and Reed (2002) — as follows:

- Consider all options with strike prices within $\mp 2.5\%$ of underlying price[22]
- Calculate best ask for put minus best bid for call
- Restrict to positive
- Calculate weighted (by volume) average
- Normalize by underlying price

4.1.4 Transaction Costs & Constraints

We use normalized bid-ask spread, the quarterly mean of daily relative bid-ask spread where daily relative bid-ask spread = (daily closing best ask − daily closing best bid)/(mid-point of daily closing best bid and best ask), as a proxy for transaction costs — see, for instance, Hasbrouck (2009).

[21] Please note that this implies that our analyses are restricted to firms that have traded options written on their equities, as one can see from the summary statistics in Table 5.1.

[22] We do sensitivity analyses for $\mp 0.5\%$ and $\mp 5\%$, and the results stay qualitatively the same.

4.1.5 Market Quality Metrics

Each market quality metric is modeled as a linear function of the exogenous factors and endogenous market activities as follows.

$$
\begin{aligned}
Metric_{i,t} \quad = \quad & \gamma + \gamma_{FINRA2241} FINRA2241_t \\
& + \gamma_{Disp} Disp_{i,t} + \gamma_{SSCC} SSCC_{i,t} + \gamma_{TrCC} TrCC_{i,t} \\
& + \gamma_{Nasdaq} Nasdaq_{i,t} + \gamma_{KOLiq} KOLiq_{i,t} + \gamma_{NormSI} NormSI_{i,t} \\
& + \gamma_{AnCov} AnCov_{i,t} + \gamma_{NormInst} NormInst_{i,t} \\
& + \gamma_{LogMCap} logMCap_{i,t} + \gamma_{logShrsOut} logShrsOut_{i,t} \\
& + \delta_{i,t}
\end{aligned}
$$

4.1.6 Endogenous Market Activities

Each endogenous market activity is modeled as a linear function of exogenous factors and other endogenous market activities, based on the market microstructure models in Kyle and Obizhaeva (2016) and Bhattacharya (2019-b), leading to seven equations, here is one example, and all are listed in Technical Appendix B.

$$
\begin{aligned}
Nasdaq_{i,t} \quad = \quad & \beta + \beta_{FINRA2241} FINRA2241_t \\
& + \beta_{Disp} Disp_{i,t} + \beta_{SSCC} SSCC_{i,t} + \beta_{TrCC} TrCC_{i,t} \\
& + \beta_{KOLiq} KOLiq_{i,t} + \beta_{NormInst} NormSI_{i,t} + \beta_{AnCov} AnCov_{i,t} \\
& + \beta_{NormInst} NormInst_{i,t} + \beta_{logMCap} logMCap_{i,t} + \beta_{logShrsOut} logShrsOut_{i.t} \\
& + \varkappa_{i,t}
\end{aligned}
$$

Table 3
Summary Statistics of All Exogenous Potential Factors And Endogenous Market Activities At Year-Quarter Level

Regressor	Number of Obs	Mean	Standard Deviation	Upper Quartile	Median	Lower Quartile
FINRA	17	0.647	0.493	1.000	1.000	0.000
Investor Valuation Dispersions	30,124	20.305	9.563	27.592	20.651	13.067
Short Sales Costs & Constraints	15,436	0.022	0.031	0.022	0.015	0.013
Transaction Costs & Constraints	32,087	0.005	0.009	0.004	0.001	0.000
Nasdaq Listing	2,330	0.614	0.487	1.000	1.000	0.000
Kyle-Obizhaeva Liquidity Measure	32,076	3,913.955	4,271.225	5,200.477	2,560.217	1,148.850
Normalized Short Interest	31,871	0.045	0.056	0.058	0.026	0.012
Analyst Coverage	30,212	346.494	475.658	390.000	193.000	84.000
Institutional Ownership of Equity	24,686	0.661	0.295	0.887	0.745	0.455
Log of Market Capitalization	32,087	20.710	2.091	22.121	20.705	19.215
Log of Shares Outstanding	32,087	17.675	1.387	18.485	17.577	16.766

We use Three Stage Least Squares (3SLS) and Errors in Variables (EiV) to account for the endogeneities and simultaneities in our model, please see Technical Appendix A for details about the cross section and time series instruments that we use for the endogenous variables and the variables measured with error.[23]

[23] Please see Liu and Saraiva (2019), Kahouli (2018), and Lee, Liang, Lin and Yang (2016), for robustness of this methodology. In particular, "under conditional homoskedasticity, GMM reduces to 3SLS if the set of instrumental variables is common to all equations." Kahouli (2018).

4.2 Total Impact of Each Exogenous Factor on Each Market Quality Metric

Given a differentiable function $F(x_1, x_2, ..., x_m, y_1, ..., y_n) : \mathbb{R}^{m+n} \longrightarrow \mathbb{R}$, where $y_j = y_j(x_1, x_2, ..., x_m), j = 1, ..., n$,

$$\begin{aligned}\frac{\mathbf{d}F(x_1, x_2, ..., x_m, y_1, ..., y_n)}{\mathbf{d}z} &= \frac{\partial F}{\partial x_1}\frac{\mathbf{d}x_1}{\mathbf{d}z} + \frac{\partial F}{\partial x_2}\frac{\mathbf{d}x_2}{\mathbf{d}z} + ... + \frac{\partial F}{\partial x_m}\frac{\mathbf{d}x_m}{\mathbf{d}z} \\ &\quad + \frac{\partial F}{\partial y_1}\frac{\mathbf{d}y_1}{\mathbf{d}z} + \frac{\partial F}{\partial y_2}\frac{\mathbf{d}y_2}{\mathbf{d}z} + ... + \frac{\partial F}{\partial y_n}\frac{\mathbf{d}y_n}{\mathbf{d}z}\end{aligned}$$

and thus, $\forall k = 1, ..., m$,

$$\begin{aligned}\frac{\mathbf{d}F}{\mathbf{d}x_k}\text{ (total impact)} &= \frac{\partial F}{\partial x_k}\text{ (direct impact)} \\ &\quad + \frac{\partial F}{\partial y_1}\frac{\mathbf{d}y_1}{\mathbf{d}x_k} + \frac{\partial F}{\partial y_2}\frac{\mathbf{d}y_2}{\mathbf{d}x_k} + ... + \frac{\partial F}{\partial y_n}\frac{\mathbf{d}y_n}{\mathbf{d}x_k} \\ &\quad \text{(indirect impact)}\end{aligned}$$

And, therefore, the total impact of each exogenous factor, such as FINRA 2241, on each market quality metric is given by the corresponding (cross-equation) total derivative as follows:

$$
\begin{aligned}
\frac{\mathbf{d}Metric}{\mathbf{d}ExogFactor} &= \frac{\partial Metric}{\partial ExogFactor} \\
&+\frac{\partial Metric}{\partial Nasdaq}\frac{\mathbf{d}Nasdaq}{\mathbf{d}ExogFactor}+\frac{\partial Metric}{\partial KOLiq}\frac{\mathbf{d}KOLiq}{\mathbf{d}ExogFactor} \\
&+\frac{\partial Metric}{\partial NormSI}\frac{\mathbf{d}NormSI}{\mathbf{d}ExogFactor}+\frac{\partial Metric}{\partial AnCov}\frac{\mathbf{d}AnCov}{\mathbf{d}ExogFactor} \\
&+\frac{\partial Metric}{\partial NormInst}\frac{\mathbf{d}NormInst}{\mathbf{d}ExogFactor}+\frac{\partial Metric}{\partial logMCap}\frac{\mathbf{d}logMCap}{\mathbf{d}ExogFactor} \\
&+\frac{\partial Metric}{\partial logShrsOut}\frac{\mathbf{d}logShrsOut}{\mathbf{d}ExogFactor} \\
&= \gamma_{ExogFactor} \\
&+\gamma_{Nasdaq}\beta_{ExogFactor}+\gamma_{KOLiq}\alpha_{ExogFactor} \\
&+\gamma_{NormSI}\theta_{ExogFactor}+\gamma_{AnCov}\zeta_{ExogFactor} \\
&+\gamma_{NormInst}\psi_{ExogFactor}+\gamma_{logMCap}\xi_{ExogFactor} \\
&+\gamma_{logShrsOut}\omega_{ExogFactor}
\end{aligned}
$$

We perform each of our analyses for 2014-September 2018 and the results are shown in Table 4 below. The impact of FINRA 2241 was statistically significantly positive for objectivity and for each of the market efficiency measures. However, please see the discussion in Bhattacharya (2024-a), on the difference between statistical significance (with huge datasets, pretty much everything is statistically significant) and actual significance,[24] and contrary to our Research Hypothesis, postulated

[24] As explained in Technical Appendix A, using the methodology discussed in Bhattacharya (2024-a), the total derivatives are all comparable, $\frac{\mathbf{d}y}{\mathbf{d}x} = \beta(y,x)$ means that a 1% increase in the cumulative probability of x causes a $\beta(y,x)$% increase in the cumulative probability of y, and similarly, $\frac{\mathbf{d}y}{\mathbf{dI}} =$

in Section 2, we find that FINRA 2241's impact on **each** of the above ten systematic and objective market quality metrics (indices of diligence, objectivity, quality, and accuracy by analysts and analyst firms, and six measures of market efficiency) was **actually insignificant at levels 1%, 0.1%, and even 0.01%**.[25]

Table 4
Total Impact of Exogenous Factors on Market Quality Metrics
(2014-September 2018)

					Market Efficiency Based On					
					Key Developments Abnormal Returns			Earnings Announcements Abnormal Returns		
	Diligence by Analyst -Analyst-Firm	Objectivity by Analyst-Analyst-Firm	Quality of Analysis by Analyst-Analyst-Firm	*Ex Post* Normalized Accuracy by Analyst-Analyst-Firm	60-Minute Announcement Window	90-Minute Announcement Window	120-Minute Announcement Window	60-Minute Announcement Window	90-Minute Announcement Window	120-Minute Announcement Window
Total Derivative of Market Efficiency with respect to										
FINRA 2241	0.00003 (0.22954)	0.00006 ** (5.67949)	-0.00002 (0.10614)	0.00005 (1.45118)	0.00011 *** (456.86028)	0.00010 *** (401.57404)	0.00010 *** (538.26999)	0.00010 *** (442.65502)	0.00010 *** (509.21045)	0.00010 *** (554.90676)
Investor Valuation Dispersions	0.03773 (0.01968)	-0.00695 (0.00169)	1.59641 *** (11.36612)	0.57713 ** (5.04875)	-0.12432 *** (10.71559)	-0.09090 ** (5.98944)	-0.11518 *** (10.05395)	-0.11595 *** (12.83125)	-0.11791 *** (14.60693)	-0.13483 *** (16.54061)
Short Sales Costs & Constraints	-1.48944 (0.80927)	-0.78291 (0.92408)	10.34386 *** (7.58061)	1.28954 (0.34046)	-0.39474 (1.24100)	-0.19620 (0.37502)	-0.31317 (0.83572)	-0.66705 ** (4.49739)	-0.67821 ** (5.09808)	-0.73010 ** (4.90167)
Transaction Costs & Constraints	-1.01275 (0.26714)	0.11193 (0.01199)	12.38745 *** (7.16898)	4.85678 ** (6.24502)	-1.05739 *** (12.26459)	-0.89211 *** (11.07738)	-1.03863 *** (13.99008)	-1.07248 *** (12.91602)	-1.06769 *** (13.22463)	-1.14817 *** (13.26113)

χ^2-statistics are reported in parentheses. ***, ** and * denote two-tailed statistical significance at 1%, 5% and 10% levels.

Actually significantly positive impacts (at level 1%) are highlighted in green and actually significantly negative impacts (at level 1%) are highlighted in red.

$\beta(y, \mathbf{I})$ where $\mathbf{I}$ is an indicator variable means that there is a $\beta(y, \mathbf{I})$ higher cumulative probability of y from $not\text{-}\mathbf{I}$ to $\mathbf{I}$. We indicate actually significantly positive impact at level of actual significance $\lambda\left(\frac{\mathbf{d}y}{\mathbf{d}x} = \beta(y, x) > \lambda\right)$, where $l = 1\%$, by green highlighting and actually significantly negative impact at level of actual significance $\lambda\left(\frac{\mathbf{d}y}{\mathbf{d}x} = \beta(y, x) < -\lambda\right)$, where $\lambda = 1\%$, by red highlighting.

[25] We have repeatedly engaged with the team of economists at FINRA to address these issues, but have not received a meaningful response. Please see Johnson and Cureton (2021), for instance, on Immanuel Kant's opinion on self-regulation being a contradiction in terms; therefore, the failure of an S.R.O. (self-regulatory organization) such as FINRA is not surprising, we thank Philip Evans for the insight.

5 Conclusions and Future Research

In this paper, we found that FINRA 2241 caused no significant improvement in market quality under each of ten separate objective and systematic metrics (indices of diligence, objectivity, quality, and accuracy by analysts and analyst firms, and six measures of market efficiency), so FINRA 2241 was not a success, bringing into question the rationale for the existence of FINRA and S.R.O.s in general.

We urge future research using our methodologies on the impacts on market quality of important capital market events such as Dot-Com Bubble (before and including 2001, potentially endogenous), Regulation Fair Disclosure (Reg FD, 2000), Sarbanes-Oxley Act (SOx, 2002), Global Analyst Research Settlements (GARS, 2003), Great Financial Crisis (GFC, 2008 and 2009, potentially endogenous), and Dodd-Frank Act (DFA, 2010).

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[dataset] CapitalIQ

[dataset] Compustat

[dataset] Compustat-CRSP Merged Database

[dataset] CRSP

[dataset] Federal Reserve of St. Louis

[dataset] I/B/E/S

[dataset] OptionMetrics

[dataset] TAQ

[dataset] Thomson Reuters

[dataset] TRACE

Technical Appendix A. Econometric Methodology

We use intraday equity trading data from TAQ and intraday fixed income security trading data from TRACE. As Kyle and Obizhaeva (2016) show, calendar-time, rather than transaction-time, is relevant for market efficiency discussions. Therefore, following Bhattacharya (2024-b, c, d), 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.

Table Appendix-0
Comparison of Intraday Data and Daily Data
(2014 - September 2018)

		Intraday Data				Daily Data		
Year	Quarter	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

The following assumption states that the public data are correlated across time, and that the $StudiedFirm$-specific actual EPS information that are unobservable to the public are correlated across time. In particular, we do not assume that a quarter's earnings model the expectation of next quarter's earnings; on the contrary, we assume that the present quarter's unknown earnings are correlated with the previous quarter's unknown earnings, which is a substantial generalization of, and therefore, a significant improvement upon, a specific formulaic model such as seasonal random walk. Let Π_{it} be the data available to the public about $StudiedFirm$ i at quarter t, **Correlation Assumption Across Time:** $\mathbf{COV}\left(\Pi_{it}, \Pi_{i(t+1)}\right) \neq 0, \mathbf{COV}\left(\aleph^*_{it}, \aleph^*_{i(t+1)}\right) \neq 0, \forall i, t.$

The following assumption states that the public data are contemporaneously correlated across $StudiedFirms$ in the same major industry sector, based, for instance, on macro factors, and that the unobserved (by the econometrician) data are contemporaneously correlated across $StudiedFirms$ in the same major industry sector, because of industry "norms" such as trade arrangements, etc., that are unobserved (by the econometrician) but common to the industry, and peer executive compensation (and across industries based on macro norms such as changes in tariff rates). This assumption also implies that $StudiedFirm$-specific actual earnings information that are unobservable to public are correlated across $StudiedFirms$ in same major industry sector. **Correlation Assumption Across Firms In Same Major Industry Sector:** $\mathbf{COV}\left(\Pi_{it}, \Pi_{kt}\right) \neq 0, k \neq i, \mathbf{COV}\left(\aleph^*_{it}, \aleph^*_{kt}\right) \neq 0, k \neq i, \forall i, t$, in same 2-digit SIC code.

In a system of equations $U = V\beta + \delta$, for a vector W to be an instrument, it is required that 1) **Strong First Stage:** $\mathbf{COV}\left(W, V\right) \neq 0$, and 2) **Exclusion Re-**

striction: COV $(W, \delta) = 0$, i.e., the unexplained part ("residual") δ of the regression needs to be uncorrelated with the instrument W — this *does not* require that the regressand U itself be uncorrelated with the instrument W. This causes the inevitable tradeoff between weakness of an instrument versus exogeneity of an instrument; see, for example, Greene (2018) and Campbell, Lo and MacKinlay (1997). In panel data econometrics, there are two popular categories of autochthonous instruments:

1. **Cross Sectional Instruments.** Instrument a variable $V_{i,t}$ by combination(s) of $V_{k,t}, k \neq i$. Cross sectional variables such as corresponding variables for other geographies have been used as instruments by, for instance, Hausman, Leonard and Zona (1994) and the validity of such instrumentation depends on the assumption that the corresponding cross sectional variables are correlated with the instrumented variable because of cost (or other) commonalities in the time period of interest but are not influenced by the idiosyncrasies of the geography of interest in the particular time period. V_{kt} (firm k in the same major industry sector as $StudiedFirm\ i$) is correlated with V_{it}. However, under the standard regularity conditions, V_{kt} is contemporaneously uncorrelated with $\left(\overleftarrow{\varepsilon_{ijt}^{*}}, \overrightarrow{\varepsilon_{ijt}^{*}}, \overleftarrow{e_{it}^{*}}, \overrightarrow{e_{it}^{*}}\right)$. Under our assumptions, therefore, the cross sectional variables are appropriate instruments. In particular, we use, as cross sectional instrument the average across the cross section excluding the particular variable, i.e., for variable $V_{(i,j),t}$ such that $\#\{k \neq (i,j)\} > 0$, we use $average_{k \neq (i,j)}(V_{k,t})$ as instrument.

2. **Time Series Instruments.** Instrument a variable $V_{i,t}$ by its lag(s) $V_{i,t-1}$, $V_{i,t-2}$, ... The use of lags as instruments depends on two implicit assumptions: a)

lack of serial correlation, see, for example, Greene (2018), and b) weak rational expectations, see, for example, Hansen and Singleton (1982).[26] $V_{i(t-\tau)}$ ($\tau \geq 1$) is correlated with V_{it}. However, under the standard regularity conditions, $V_{i(t-\tau)}$ ($\tau \geq 1$) is uncorrelated with $\left(\overleftarrow{\varepsilon^*_{ijt}}, \overrightarrow{\varepsilon^*_{ijt}}, \overleftarrow{e^*_{it}}, \overrightarrow{e^*_{it}}\right)$. Under our assumptions, therefore, the lagged variables are appropriate instruments. In particular, we use as time series instrument the first lag of the relevant variable, i.e., for variable $V_{i,t}$, we use $V_{i,t-1}$ as instrument.

As Wooldridge (2010) points out, most of the problems with using instrumental variables arise in small samples, which is not the case in this paper. Wooldridge (2010) points out that "asymptotically, we can do no worse, and can often do better, using a larger set of valid instruments." Given these two critical qualifications, we consider in this paper both of the above instrumentation categories to ensure that our conclusions are not sensitive to particular information assumptions.

For each ticker and $Analyst\text{-}AnalystFirm$, we require at least 7 observations (i.e., at least 7 quarters of data) to calculate the index of diligence, and for each ticker and $Analyst\text{-}AnalystFirm$, we require at least 8 observations (i.e., at least 2 years of data) to calculate the index of objectivity. For each index, therefore, we use rolling calculations for eight consecutive quarters prior to and including the quarter of interest.

Following Bhattacharya (2024-a), when dealing with large numbers of observations, we replace each variable x, except for each indicator or time variable, by its normalization $\Phi\left(Z\text{-}Score\left(x\right)\right) = \Phi\left(\frac{x - Mean(x)}{StDev(x)}\right)$, where Φ is the cumulative proba-

[26]Roberts and Whited (2011) show that the traditional statistical tests for the use of lagged variables in panel estimation are not particularly useful, so we do not use them in this paper.

bility function of a standard Gaussian random variable. 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.[27] 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 associated with belonging in $\mathbf{N}$, and a regression coefficient $\beta(y,\mathbf{t})$ on the regression of the regressand y on time $\mathbf{t}$ means that there is a $\beta(y,\mathbf{t})$ increase in cumulative probability of y from one time period to the next. The association of a regressor x with the regressand y is **actually significantly positive at level of actual significance** λ if the relevant coefficient[28] $\beta(y,x) > \lambda$ and is **actually significantly negative at level of actual significance** λ if the relevant coefficient $\beta(y,x) < -\lambda$. We indicate actually significantly positive associations at 1% level by green highlighting and actually significantly negative associations at 1% level by red highlighting.

[27] $Percentile\,(x) \simeq RoundUp\,(100\Phi\,(Z\_Score\,(x)))$ 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.

[28] Please see Aman, et. al., (2019) for a robust defense of "responsible science," that science needs to have integrity and relevance.

Technical Appendix B. Structural System

$$
\begin{aligned}
Metric_{i,t} \;=\; & \gamma + \gamma_{FINRA2241} FINRA2241_t \\
& + \gamma_{Disp} Disp_{i,t} + \gamma_{SSCC} SSCC_{i,t} + \gamma_{TrCC} TrCC_{i,t} \\
& + \gamma_{Nasdaq} Nasdaq_{i,t} + \gamma_{KOLiq} KOLiq_{i,t} + \gamma_{NormSI} NormSI_{i,t} \\
& + \gamma_{AnCov} AnCov_{i,t} + \gamma_{NormInst} NormInst_{i,t} \\
& + \gamma_{LogMCap} logMCap_{i,t} + \gamma_{logShrsOut} logShrsOut_{i,t} \\
& + \delta_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
Nasdaq_{i,t} \;=\; & \beta + \beta_{FINRA2241} FINRA2241_t \\
& + \beta_{Disp} Disp_{i,t} + \beta_{SSCC} SSCC_{i,t} + \beta_{TrCC} TrCC_{i,t} \\
& + \beta_{KOLiq} KOLiq_{i,t} + \beta_{NormInst} NormSI_{i,t} + \beta_{AnCov} AnCov_{i,t} \\
& + \beta_{NormInst} NormInst_{i,t} + \beta_{logMCap} logMCap_{i,t} + \beta_{logShrsOut} logShrsOut_{i.t} \\
& + \varkappa_{i,t}
\end{aligned}
$$

$$\begin{aligned}
KOLiq_{i,t} &= \alpha + \alpha_{FINRA2241} FINRA2241_t \\
&+ \alpha_{Disp} Disp_{i,t} + \alpha_{SSCC} SSCC_{i,t} + \alpha_{TrCC} TrCC_{i,t} \\
&+ \alpha_{Nasdaq} Nasdaq_{i,t} + \alpha_{NormSI} NormSI_{i,t} + \alpha_{AnCov} AnCov_{i,t} \\
&+ \alpha_{NormInst} NormInst_{i,t} + \alpha_{logMCap} logMCap_{i,t} + \alpha_{logShrsOut} logShrsOut_{i,t} \\
&+ \varepsilon_{i,t}
\end{aligned}$$

$$\begin{aligned}
NormSI_{i,t} &= \theta + \theta_{FINRA2241} FINRA2241_t \\
&+ \theta_{Disp} Disp_{i,t} + \theta_{SSCC} SSCC_{i,t} + \theta_{TrCC} TrCC_{i,t} \\
&+ \theta_{Nasdaq} Nasdaq_{i,t} + \theta_{KOLiq} KOLiq_{i,t} + \theta_{NormInst} NormSI_{i,t} \\
&+ \theta_{AnCov} AnCov_{i,t} + \theta_{logMCap} logMCap_{i,t} + \theta_{logShrsOut} logShrsOut_{i,t} \\
&+ \eta_{i,t}
\end{aligned}$$

$$\begin{aligned}
AnCov_{i,t} &= \zeta + \zeta_{FINRA2241} FINRA2241_t \\
&+ \zeta_{Disp} Disp_{i,t} + \zeta_{SSCC} SSCC_{i,t} + \zeta_{TrCC} TrCC_{i,t} \\
&+ \zeta_{Nasdaq} Nasdaq_{i,t} + \zeta_{KOLiq} KOLiq_{i,t} + \zeta_{NormInst} NormSI_{i,t} \\
&+ \zeta_{NormInst} NormInst_{i,t} + \zeta_{logMCap_{i,t}} logMCap_{i,t} + \zeta_{logShrsOut} logShrsOut_{i,t} \\
&+ \vartheta_{i,t}
\end{aligned}$$

$$
\begin{aligned}
NormInst_{i,t} \;=\;& \psi + \psi_{FINRA2241} FINRA2241_t \\
& + \psi_{Disp} Disp_{i,t} + \psi_{SSCC} SSCC_{i,t} + \psi_{TrCC} TrCC_{i,t} \\
& + \psi_{Nasdaq} Nasdaq_{i,t} + \psi_{KOLiq} KOLiq_{i,t} + \psi_{NormInst} NormSI_{i,t} \\
& + \psi_{AnCov} AnCov_{i,t} + \psi_{logMCap_{i,t}} logMCap_{i,t} + \psi_{logShrsOut} logShrsOut_{i,t} \\
& + \nu_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
logMCap_{i,t} \;=\;& \xi + \xi_{FINRA2241} FINRA2241_t \\
& + \xi_{Disp} Disp_{i,t} + \xi_{TrCC} TrCC_{i,t} + \xi_{SSCC} SSCC_{i,t} \\
& + \xi_{Nasdaq} Nasdaq_{i,t} + \xi_{KOLiq} KOLiq_{i,t} + \xi_{NormInst} NormSI_{i,t} \\
& + \xi_{AnCov} AnCov_{i,t} + \xi_{NormInst} NormInst_{i,t} + \xi_{logShrsOut} logShrsOut_{i,t} \\
& + \upsilon_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
logShrsOut_{i,t} \;=\;& \omega + \omega_{FINRA2241} FINRA2241_t \\
& + \omega_{Disp} Disp_{i,t} + \omega_{SSCC} SSCC_{i,t} + \omega_{TrCC} TrCC_{i,t} \\
& + \omega_{Nasdaq} Nasdaq_{i,t} + \omega_{KOLiq} KOLiq_{i,t} + \omega_{NormInst} NormSI_{i,t} \\
& + \omega_{AnCov} AnCov_{i,t} + \omega_{NormInst} NormInst_{i,t} + \omega_{logMCap} logMCap_{i,t} \\
& + \varrho_{i,t}
\end{aligned}
$$

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