Exploring the Impact of Information Asymmetry on Market Efficiency

Saif Moolji[1], Aaron Villanueva[2], and Tony Zhong[2]

[1]ICME, Stanford University
[2]Department of Statistics, Stanford University

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Abstract

This paper examines the effect of sell-side equity research on market quality, measured by liquidity, risk, and price efficiency. We construct an instrumental variable using a list of 16 brokerage merger events between 2008 and 2023 to act as exogenous shocks to analyst coverage, where acquired firm's research operations are absorbed and cease to independently exist. Combining I/B/E/S forecast data with CRSP trading data, we apply a two-stage least squares approach to isolate the effect of coverage on each of our designated outcome variables from endogenous firm characteristics. We find strong first-stage F-statistics (= 39.9), indicating significant instrument strength. In our second-stage results, we find that higher analyst coverage has a causal positive impact on both market efficiency and liquidity, the latter result in line with [Kelly and Ljungqvist, 2012]. Specifically, exogenous increases in coverage reduce the Hou-Moskowitz price-delay measure, indicating faster incorporation of market-wide information, while also narrowing bid-ask spreads, consistent with more liquid markets. These results are largely invisible in naive OLS regressions, but become significant under the IV strategy. By contrast, coverage has little effect on crash risk as measured by NCSKEW and DUVOL, suggesting that analyst research primarily improves day-to-day trading efficiency rather than extreme tail events. Our results highlight that sell-side equity research does reduce information asymmetry and improve market outcomes and suggests that declines in coverage may carry real costs for market quality.

1 Introduction

We aim to determine whether sell-side equity research has a causal effect on market efficiency by reducing information asymmetry among market participants. Various market participants have access to different kinds of information. Firms such as hedge funds, pension funds, and mutual funds employ buy-side analysts to produce proprietary equity research to inform their investment decisions. This process entails both sourcing investment opportunities and forecasting company financials. Since these institutions have different mandates, incentives, and investing horizons, the manner in which they process information, and the research they produce can vary greatly [Wang et al., 2023]. On the other hand, institutions such as banks and brokerage firms employ sell-side analysts to cover a specific list of companies and provide periodic research reports to clients. These reports include both qualitative and quantitative information such as written reports, predictions for firm financials, a price estimate, as well as a buy, hold, or sell recommendation. Institutions can purchase these reports, either directly or indirectly by soft-dollar payments, or access publicly available consensuses that aggregate various firm forecasts.

Empirical research suggests that institutional investment decisions are highly correlated with the kinds of recommendations offered by sell-side equity reports [Kong et al., 2021]. The main question this study seeks to answer is whether these reports offer additional information that is not already captured in asset prices. We will do this by examining the impact of such reports on overall market quality, as measured by three metrics: asset liquidity, price efficiency, and market risk. We aim to determine whether analyst coverage improves investor confidence in trading those assets, thereby increasing liquidity, and making it cheaper and easier for investors across the board, even those that do not have access to such reports, to trade. Similarly, we wish to see whether this additional information makes markets more efficient, thereby increasing the speed with which asset prices reflect information, making it easier and cheaper to trade, and reducing uncertainty. Finally, we wish to explore the effect of coverage on more direct measures of uncertainty and risk. Even if coverage reduces trading costs, market quality arguably does not improve if analyst-induced herding exacerbates the likelihood of adverse events, such as market crashes. Consequently, we estimate the Local Average Treatment Effect (LATE) of analyst coverage on liquidity, efficiency, and crash risk.

The main challenge in estimating such a causal effect is endogeneity. Consider a simple linear regression estimating the effect of analyst coverage (Z) on stock liquidity (Y):

$$Y = \tau Z + \varepsilon$$

where τ represents the causal effect of coverage on liquidity and ε is our error term. In this specification, the treatment and error terms are likely correlated due to endogeneity. First, omitted variable bias presents a significant challenge; unobserved factors likely influence both coverage and the response variable. For example, higher volatility, more glamorous stocks are more likely to be covered by sell-side analysts [Lee and So, 2017], while volatility can also impact liquidity [Liu et al., 2016]. Various other omitted variables, such as changes in the riskiness of the firm's cash flows [Kelly and Ljungqvist, 2012] impact both coverage and liquidity. There additionally exists a reverse causality issue, since firms often choose to cover stocks that are more liquid in the first place [Kelly and Ljungqvist, 2012]. Furthermore, treatment assignment is non-random due to selection bias, given that analysts may choose to cover stocks based on their performance. In fact, coverage termination can empirically be viewed as equivalent to a sell recommendation, since firms will very often stop coverage for underperforming stocks [Scherbina, 2007].

While discussed here in the context of liquidity, these endogeneity concerns apply equally to price efficiency and crash risk. Price delay (as a measure for how quickly markets incorporate information) as well as crash risk are also impacted by omitted variables, since the firm characteristics identified above (and also variables such as size and volatility) that impact analyst coverage also affect those variables. Both are also similarly subject to selection bias, since brokerages may cover stocks that are less subject to large crashes and or where prices are slower to be incorporated. To address these challenges in identifying a causal effect, we will identify and utilize brokerage closure events as exogenous shocks to analyst coverage to construct an instrumental variable to isolate the impact of coverage on each of these outcomes.

2 Related Work

Our identification strategy builds primarily upon [Kelly and Ljungqvist, 2012], who construct a similar instrument using a list of 43 identified merger and closure events for brokerage firms from 2000 to Q1 2008. They provide evidence over this period that uninformed demand and asset prices respond to variations in information availability, highlighting the effect of these frictions on liquidity. Our work will update this instrument using similar merger events over the period ranging from 2008 to 2023. However, we exclude closure events to explicitly test the instrument strength of merger events alone, as detailed in Section 4. We also expand beyond just liquidity as a measure for market health. We employ the Hou-Moskowitz delay measure [Hou and Moskowitz, 2005] to see how quickly markets incorporate information, which effectively acts as a proxy for market efficiency more broadly. We also examine the causal impact of sell-side equity research on the risk of market crashes, as defined by [Chen et al., 2001], to determine if reports causally reduce the frequency of adverse tail events driven by information asymmetry. Other similar research exists exploring the impact of information asymmetry through a loss in analyst coverage on firm-specific decision making in terms of investment and financing decisions [Derrien and Kecskés, 2013].

Recent work has also emphasized the relevance of sell-side equity research in the post-GFC environment. Evidence suggests that sell-side analyst coverage has declined since the 2008 financial crisis [Hettler et al., 2023], raising concerns about potential negative consequences for market efficiency and firm-level outcomes. If analyst reports provide a causal increase in liquidity or a reduction in the risk of market crashes, such declines underscore the importance of policies or mechanisms to maintain adequate coverage. Lastly, there has been additional recent research into the breakdown of what kinds of analyst reports as well as the components of those reports are most valuable to institutional investors [Lv, 2024], which underscores the significance in affirming that such reports provide investors with additional information compared to their own proprietary research.

3 Data

We used three main data sources. First, we used the SDC Platinum M&A dataset available through the London Stock Exchange Group (LSEG) to identify a list of brokerage firm mergers over our designated period from Q1 2008 to Q4 2023. We only examined brokerage firms located in the United States, and limited ourselves to major merger events, meaning acquisitions of brokerage firms with greater than $50 million in net debt. We then manually identified the firms of those remaining that had equity research branches, and ensured those equity research branches were absorbed into existing research structures by the acquiring firm. For instance, when Barclays acquired Lehman Brothers in 2008, they simply took over Lehmann's equity research division in the United States, since they did not have one previously [Kelly and Ljungqvist, 2012]. Consequently, we excluded these transactions from our instrument set.

We used the I/B/E/S dataset for a comprehensive list of all analyst forecasts produced between 2008 and 2023. As our primary interest lies in the aggregate coverage per stock, the relevant I/B/E/S data fields were: the brokerage firm responsible for the estimate, the date the estimate was announced, and the official ticker of the stock for which the estimate was produced. Since 2008, I/B/E/S has anonymized both analyst names and brokerage firm names associated with each individual forecast via ID numbers. Despite claims that these IDs had also been shuffled, research suggests that there is no evidence this actually took place [Law, 2022], which meant it was possible for us to back out the names of relevant brokerage firm IDs based on when brokerage ID numbers disappeared from the dataset. Given a list of merger events, more specifically, the firms that were acquired in these events, and their announcement date, we checked a period of 90 days before and 7 days after each announcement date, since firms may have ceased research operations slightly before their merger was officially announced. The brokerage ID code that ceased operations within that period was then matched with the firm acquired over that period. Figure 1 illustrates this identification process for Brokerage ID 1523, whose monthly estimates drop to zero the same month as the merger date for Sandler O'Neill. The full list of merger events used can be seen in the appendix. We then used the CRSP dataset for daily price data for each of the securities associated with a coverage drop from a brokerage merger event, including stock tickers and CUSIPs (for merging with I/B/E/S), bid and ask values, daily trading volume, daily return, the de-listed return, as well as shares outstanding.

4 Methods

4.1 Identification Strategy

Estimating the causal effect of analyst coverage on market quality is challenging due to endogeneity. As outlined earlier, analysts typically select firms that are already liquid and efficient, creating a selection bias that biases naive OLS estimates toward zero. To address this, we exploit a natural experiment to identify exogenous shocks to analyst coverage that satisfy three conditions:

- **Independence:** The instrument must be independent of potential outcomes and unobserved confounders.
- **Relevance:** The instrument must induce significant variation in the treatment (analyst coverage).
- **Exclusion Restriction:** The instrument must affect the outcome *only* through the treatment (analyst coverage), and not through other channels.

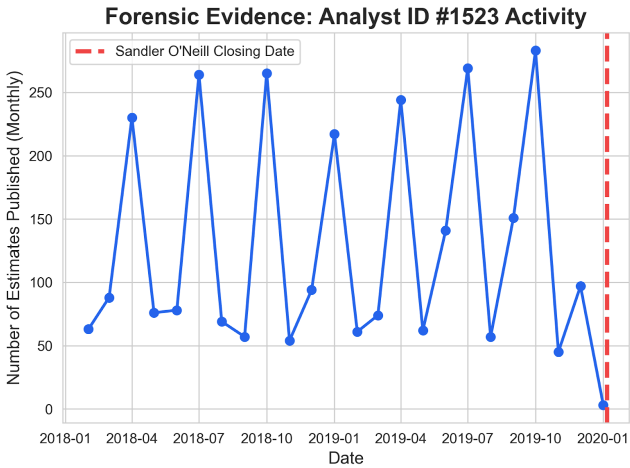

Figure 1: ID # 1523 drops to zero estimates at the merger date for Sandler O'Neill which closed Jan 2020.

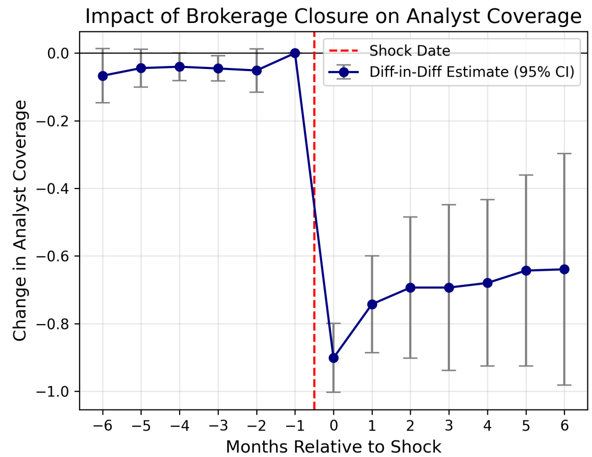

Figure 2: Analyst coverage drops immediately following merger events.

Satisfaction of these criteria is required for a valid instrumental variable (IV) estimator. As noted earlier, the instrument we will use are brokerage merger events, where one firm acquires another, who then ceases their equity research activities. There are two separate kinds of merger events we might see. The first case is when both firms prior to the merger cover a given stock, and afterwards continue to cover that stock. This event represents an exogenous shock to analyst coverage, since the loss of coverage is unrelated to characteristics about the stock or any of the other confounding factors - a reduction in reports occurs strictly due to consolidation. The second kind of merger event is when only one of the two firms cover a particular stock before the merger, and then the firm decides to cover that stock post-merger. This does not represent an exogenous shock to coverage, since the number of published reports about that given stock may not change in the first place. Additionally, given the discrepancy in coverage between the two firms, the merger requires a joint decision about whether to cover that stock, which is subject to selection bias, and therefore victim to potential endogeneity [Kelly and Ljungqvist, 2012]. As a result, we only examine the first type of merger event for our instrument.

It is important to note that brokerage closure events are also valid exogenous shocks, since the closure of a firm also represents a loss of analyst coverage independent of the confounding variables. In fact, the original paper [Kelly and Ljungqvist, 2012] includes both closure events and the exogenous type of merger identified above. This study excludes closure events for two main reasons. First of all, we wish to examine the instrument strength of these merger events alone to validate their initial inclusion in the original instrument. If, for example, we find the instrument is particularly weak, or the causal effect we identify is small, it might suggest that solely using brokerage closures might make for a more effective instrument. Secondly, the merger events were far easier to identify, since they exist in centralized dataset, while the closure events require examining the monthly FINRA reports on firms they no longer regulate.

We now examine whether the brokerage merger instrument satisfies the relevance and exclusion restriction conditions. The instrument satisfies the relevance condition by construction, since a cessation of operations by the acquired firm means a reduction in analyst reports published for the stocks they covered, meaning a reduction in coverage. The exclusion restriction requires more careful justification. The large banks we consider as a part of our instrument that offer sell-side equity research are also market-makers (also called liquidity-providers), meaning they quote bid and ask prices for various securities along with associated volumes for each side of the market. As a result, in instances where the acquired firm was a market maker in addition to providing sell-side research, it is possible that we would see a reduction in liquidity because of a loss of market-making volume (reducing supply and therefore widening bid-ask spreads). To address this, we could either exclude such merger events from our instrument, or, as detailed below, control for the reduction in market making volume resulting from a merger event when estimating the impact of a loss of coverage on liquidity. To maximize statistical power while maintaining validity, we adopt the latter approach by including Turnover Ratio as a control variable. By holding trading volume turnover constant, we effectively separate the "information channel" (the impact of the analyst's research) from the "inventory channel" (the loss of market-making supply), thereby satisfying the exclusion restriction.

4.2 Instrument Construction

Having identified the list of relevant mergers for our instrument, we will now discuss its construction. For each brokerage merger, we define the pre-shock window as 6 months prior to the closure date. We consider stocks covered in this window as treated. We also only consider stocks that have ≥ 3 analysts and ≤ 15 analysts (in median) covering it during this time. Stocks with too few analysts covering them already have thin coverage, so losing one broker may not represent a meaningful change in information availability (i.e. people may not be willing to trade based off of the recommendations of one analyst). Similarly, stocks with very high coverage have redundant information, so the loss of one particular firm's estimates may not produce a meaningful change in information availability.

Next, we constructed a set of control stocks for each treated stock. Control stocks were selected from the set of active stocks not covered by the closing broker during the pre-shock window. To improve balance, we match controls on pre-shock total analyst coverage, allowing only those with ± 2 analysts of the median coverage of the treated stocks to be controls. If insufficient matches exist, we select the remaining controls randomly from the pool of active stocks. This matching ensures that any observed differences in coverage post-shock are attributable to the broker closure rather than preexisting differences in analyst coverage. Once treated and control stocks are identified, we construct a monthly event panel spanning six months before and six months after the closure. For each stock in the panel, we calculated the censored coverage, which excludes contributions from the departed broker in the post-shock period. Each observation is given two labels: `treated` (which is 1 for stocks affected by the closure and 0 otherwise) and `post` (which is 1 for months following the closure and 0 for pre-shock months). We define the instrument Z_{it} as follows:

$$Z_{it} = \texttt{treated}_{it} \cdot \texttt{post}_{it}$$

Intuitively, $Z_{it} = 1$ represents the portion of analyst coverage that changes exogenously due to the broker closure, which allows us to isolate variation in coverage that is independent of firm-specific characteristics. We will use this in the first stage of our two-stage least squares regression to predict analyst coverage (D_{it}), which is just the number of analysts covering stock i at a given time t.

4.3 Local Average Treatment Effect Estimation

Using the instrument Z constructed from brokerage merger events, we will estimate the treatment D of analyst coverage as well as our treatment effect τ of analyst coverage on liquidity Y. We will measure liquidity via a bid-ask spread, calculated as follows:

$$Y_i = \frac{(\textbf{Ask})_i - (\textbf{Bid})_i}{(\textbf{Midpoint Price})_i}$$

Where our Midpoint Price is given as:

$$(\textbf{Midpoint Price})_i = \frac{(\textbf{Ask Price})_i + (\textbf{Bid Price})_i}{2}$$

We also identified a number of covariates (X) to include in our regression analyses: Firm Size, Return on Assets, Leverage, Market to Book Ratio, R&D Intensity, and Turnover Ratio (exact calculations for these metrics can be found in the appendix). The first five covariates are various stock characteristics we wish to control for, while the turnover ratio is our way of controlling for the decrease in market making volume at a given time, which we wish to do if market making operations cease as a result of the merger. Each of our variables vary both with the stock (which we index by i) and time (which we index by t). We will thus also include fixed effects for both time (δ_t) to control for changing macro environments over time and the industry (θ_i) the stock is in to control for industry specific characteristics that vary. With this in mind, the setup of our two-stage least squares to estimate is as follows:

Stage 1:

$$D_{it} = \pi_0 + \pi_1 Z_{it} + \pi_2^T X_{it} + \delta_t + \theta_i + u_{it}$$

Stage 2:

$$Y_{it} = \alpha + \tau \hat{D}_{it} + \gamma^T X_{it} + \delta_t + \theta_i + \varepsilon_{it}$$

In the first stage, we fit a regression using our instrument Z_{it}, the covariates X_{it} and fixed effects δ_t and θ_i on our outcome variable, which is the total number of analyst forecasts provided for stock i at a given time t. We then use the vector of fitted values from stage 1, $\hat{D}_{it}$, in our second stage regression to estimate τ, the desired local average treatment effect of analyst coverage on liquidity.

4.4 Alternative Outcome Variable Construction

To capture market efficiency, we calculate the Price Delay measure proposed by [Hou and Moskowitz, 2005]. For each stock-month, we estimate two regressions using daily returns. The unrestricted model regresses stock returns on the market return and four weeks of lagged market returns, while the restricted model includes only the contemporaneous market return. Price Delay is defined as:

$$\text{Delay}_i = 1 - \frac{R^2_{\text{restricted}}}{R^2_{\text{unrestricted}}}$$

A higher Delay indicates that the stock price incorporates market-wide information more slowly. If analyst coverage improves efficiency, we expect a negative causal coefficient.

To measure risk, specifically the likelihood of extreme negative tail events (crash risk), we follow [Chen et al., 2001] and calculate the Negative Coefficient of Skewness (NCSKEW) and the Down-to-Up Volatility (DUVOL). We first isolate firm-specific daily returns by regressing total returns on the value-weighted market index and its lags. Using the residuals ($\varepsilon_{i,t}$) from this regression, we calculate NCSKEW as the third moment of the residuals, normalized by the standard deviation. A higher NCSKEW indicates a distribution with a longer left tail, signifying higher crash risk.

5 Experiments

5.1 First-Stage Diagnostics

We begin by verifying the validity and strength of our instrument. For the brokerage merger instrument to be effective, it must induce a sharp and significant variation in analyst coverage (Relevance) while satisfying the parallel trends assumption prior to the shock. Figure 2 visualizes the results of an event study regression, tracking analyst coverage for treated firms relative to controls in the months surrounding the merger event ($t = 0$). In the pre-shock period ($t < 0$), the difference-in-differences coefficients are statistically indistinguishable from zero. This confirms the parallel trends assumption, indicating that treated and control firms followed similar coverage trajectories prior to the merger.

At the time of the merger ($t = 0$), we observe an immediate, sharp, and persistent drop in coverage for the treated group. To formally test instrument strength, we regress total coverage on our instrument (Z_{it}) and controls. The first-stage regression yields a Kleibergen-Paap rk Wald F-statistic of 39.90, which well exceeds the standard rule-of-thumb threshold of 10 proposed by [Stock and Yogo, 2005], as well as more conservative critical values. This indicates that our instrument is sufficiently strong to avoid weak-instrument bias.

5.2 Main Results: Efficiency and Liquidity

Having established a strong first stage, we estimate the causal effect of analyst coverage on market quality using Two-Stage Least Squares (2SLS). Table 1 compares these causal estimates with naive OLS baselines.

Price Efficiency: We measure efficiency using the Hou-Moskowitz Price Delay metric, where a lower value indicates faster information incorporation. As shown in Panel A, the naive OLS estimate is near zero and statistically insignificant ($\beta = -0.0008$). However, the IV estimate is negative and statistically significant ($\beta = -0.0561$, $t = -3.44$). This implies that an exogenous loss of coverage causes prices to adjust more slowly to new information. The discrepancy between the OLS and IV results suggests that the OLS estimates are biased toward zero, likely because analysts endogenously select to cover firms that are naturally more efficient or liquid, masking the marginal benefit of their research.

Table 1: Impact of Analyst Coverage

Outcome	Model	Coef (β)	SE	t-stat
Panel A: Price Efficiency (Delay)				
	OLS	-0.0008	0.002	-0.37
	IV	**-0.0561*** **	**0.016**	**-3.44**
Panel B: Liquidity (Spread)				
	OLS	0.0000	0.000	0.55
	IV	**-0.0005** **	**0.000**	**-2.39**
Panel C: Crash Risk (NCSKEW)				
	OLS	0.0016	0.006	0.26
	IV	-0.0293	0.048	-0.60

Controls: Size, ROA, Lev, MTB, Opaque, Turn.
* p<0.1, ** p<0.05, *** p<0.01

Liquidity: A similar pattern emerges for liquidity in Panel B. The OLS estimate for Bid-Ask Spreads is effectively zero ($t = 0.55$). In contrast, the IV estimate is negative and significant ($\beta = -0.0005$, $t = -2.39$). This indicates that analyst coverage plays a causal role in reducing information asymmetry, leading to tighter spreads and lower transaction costs for investors.

5.3 Crash Risk and Volatility

We investigate whether the information provided by analysts mitigates the risk of extreme tail events. As shown in Panel C, we find no causal evidence that analyst coverage impacts crash risk. The coefficient for NCSKEW is negative ($\beta = -0.0293$), suggesting a reduction in crash risk, but it is statistically insignificant ($t = -0.60$). We observed similar statistically insignificant results for Down-to-Up Volatility (DUVOL) and total return volatility ($\beta = -0.0202$, $t = -1.48$). This null result is economically significant. It suggests that while sell-side research improves continuous market functioning—by enhancing price efficiency and liquidity—it does not necessarily alter the structural probability of sudden, extreme market crashes.

5.4 Robustness Checks

A potential concern with the standard 2SLS approach is that linear controls may not fully account for fundamental differences between treated and control firms. To address this, we implement Propensity Score Matching (PSM). We estimate the probability of treatment based on pre-shock characteristics (Size, ROA, Leverage, Market-to-Book, and Opaqueness) and match each treated firm to a control firm with the closest propensity score.

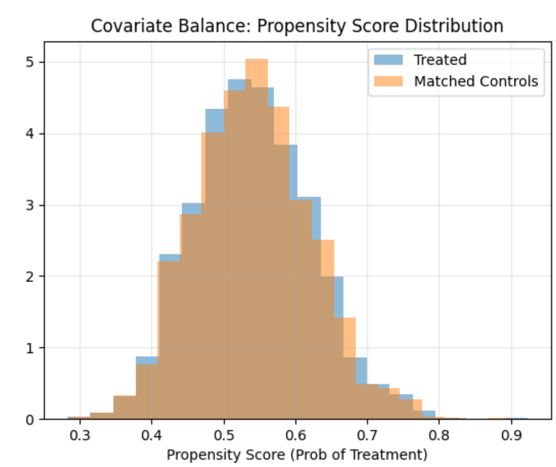

Figure 3: Covariate Balance: Propensity Score Dist.

Figure 3 demonstrates the covariate balance achieved after matching. The overlapping distributions indicate that our treated and matched control groups are highly comparable in terms of observable fundamentals. We re-run our IV analysis on this strictly matched subsample ($N = 18,636$). The results for price efficiency remain robust ($\beta = -0.0632$,

$t = -3.38$), confirming that our primary findings are driven by the exogenous shock rather than functional form misspecification, while the liquidity results, though directionally consistent, are more sensitive to sample size reduction.

6 Conclusion

This paper examines whether sell-side analyst coverage has a causal impact on market efficiency and related dimensions of market quality. Building on the strategy of [Kelly and Ljungqvist, 2012], we construct an instrument based on U.S. brokerage mergers between 2008 and 2023, which result in exogenous reductions in analyst coverage that are plausibly orthogonal to the firm's own fundamentals.

By applying this instrument via two-stage least squares, we find that analyst coverage has statistically significant effects on price efficiency and liquidity. In particular, higher coverage significantly reduces the Hou-Moskowitz price-delay measure, implying that following exogenous increases in analyst research, prices adjust more quickly to market-wide information. Coverage also leads to narrower proportional bid–ask spreads - i.e., more liquid markets. Noticeably, these effects are largely invisible in naive OLS regressions (where endogeneity biases the estimated coefficients toward zero), but they become apparent once we isolate the variation in coverage induced by mergers. The main findings survive when we re-estimate the model on a propensity-score-matched subsample of treated and control firms. By contrast, we do not find strong evidence that coverage materially affects crash risk or overall volatility. In our setting, sell-side research appears to operate primarily through continuous margins of market quality (e.g., faster information incorporation and lower spreads) rather than through large changes in the probability of extreme downside events.

Importantly, the above results should be treated as local to the types of firms and events we study, i.e., mid-coverage U.S. stocks affected by large brokerage mergers in the post-crisis period. They do not necessarily generalize to small firms with thin coverage or settings with large coordinated changes in coverage. Moreover, the exclusion restriction for the instrument relies on the assumption that any market-changing activities associated with mergers are adequately controlled for by turnover and other covariates, which needs further verification. Nevertheless, the evidence presented in this paper contributes to a growing body of work emphasizing the informational role of sell-side equity research. If analyst coverage causally improves price efficiency and reduces trading frictions, then the documented decline in coverage in the post-GFC era [Hettler et al., 2023] may carry real costs for market quality. Some directions for future work include extending the present analysis to broker closures, examining heterogeneity in effects across different firm sizes and sectors, and decomposing which components of analyst output (e.g., earnings forecasts, target prices, qualitative commentary) are most responsible for the improvements in market efficiency documented in this study.

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A Brokerage Mergers

Table 2: Brokerage Mergers Used for Instrument Construction

Broker Name	**Merger Date**
Merrill Lynch & Co Inc	January 1, 2009
Fox-Pitt Kelton Cochran Caronia Waller	October 2, 2009
Wachovia Securities Financial Holdings LLC	December 31, 2009
Thomas Weisel Partners Group Inc	July 1, 2010
Morgan Keegan & Co Inc	April 2, 2012
KBW Inc	February 15, 2013
Knight Capital Group Inc	July 1, 2013
International Strategy & Investment Group LLC	October 31, 2014
SWS Group Inc	January 1, 2015
Sterne Agee Group Inc	June 5, 2015
Simmons & Co International	February 29, 2016
Leerink Holdings LLC	January 4, 2019
Sandler O'Neill Partners LP	January 6, 2020
Ladenburg Thalmann Financial Services Inc	February 14, 2020
JMP Group Inc	November 15, 2021
Cowen Inc	March 1, 2023

B Covariate Calculations

The following covariates were used in the two-stage least squares analysis:

- $\textbf{Firm Size} = \log(\textbf{Total assets})$
- $\textbf{Return on Assets} = \frac{\textbf{Net Income}}{\textbf{Total Assets}}$
- $\textbf{Leverage} = \frac{\textbf{Total Debt}}{\textbf{Total Assets}}$
- $\textbf{Market to Book} = \frac{\textbf{Market Cap}}{\textbf{Common Equity}}$
- $\textbf{R\&D Intensity} = \frac{\textbf{R\&D Expenditure}}{\textbf{Total Assets}}$
- $\textbf{Turnover Ratio} = \frac{\textbf{Daily Volume}}{\textbf{Shares Outstanding}}$

C Github Link

All code for this project can be found at:
`https://github.com/RichardFeynmanEnthusiast/stats-209-final-project-code/tree/main`