The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXXII, NO. 3 • JUNE 2017

Does the Scope of the Sell-Side Analyst Industry Matter? An Examination of Bias, Accuracy, and Information Content of Analyst Reports

KENNETH MERKLEY, RONI MICHAELY, and JOSEPH PACELLI*

ABSTRACT

We examine changes in the scope of the sell-side analyst industry and whether these changes impact information dissemination and the quality of analysts' reports. Our findings suggest that changes in the number of analysts covering an industry impact analyst competition and have significant spillover effects on other analysts' forecast accuracy, bias, report informativeness, and effort. These spillover industry effects are incremental to the effects of firm level changes in analyst coverage. Overall, a more significant sell-side analyst industry presence has positive externalities that can result in better functioning capital markets.

SELL-SIDE FINANCIAL ANALYSTS PLAY an important role in capital markets. Analysts facilitate the distribution of financial information, and their reports provide valuable information to market participants (e.g., Grossman and Stiglitz (1980), Womack (1996), Kadan et al. (2009), Loh and Stulz (2011)). Further, analysts help shape capital markets through their interactions with underwriters, brokers, institutional investors (IIs), and management. It is not surprising therefore that the behavior of analysts has captured the attention of many academic studies. These prior studies consider various aspects of analysts' activities such as their choice to cover particular firms (Jegadeesh et al. (2004)) and how the intensity of such coverage can influence firms' information environments and financial policies (e.g., Hong and Kacperczyk (2010), Derrien and Kecskés (2013), Balakrishnan et al. (2014)).

Despite the significant interest in financial analysts, there is surprisingly little empirical evidence examining the sell-side analyst industry as a whole.

*Kenneth Merkley is at the Samuel Curtis Johnson School of Management, Cornell University. Roni Michaely is at the Samuel Curtis Johnson School of Management and Cornell Tech. Joseph Pacelli is at the Kelley School of Business, Indiana University. We thank Kristian Allee and Matthew DeAngelis for assisting us with conference call data. We benefited from comments and suggestions received from Joseph Comprix, François Degeorge, François Derrien, Janet Gao, Roger Loh, Jay Ritter, Alex Tebay, and Richard Willis and seminar participants at the 2014 American Finance Association annual meeting, Cornell University, Georgia State University, the Interdisciplinary Center (Herzliya, Israel), Singapore Management University, the University of Delaware, the University of Kentucky, the 2014 Financial Accounting Reporting Section midyear meeting, and the 2013 New York Accounting and Finance Forum. The authors have no conflicts of interest, as identified by the *Journal of Finance*'s disclosure policy.

DOI: 10.1111/jofi.12485

In particular, we know little about which economic factors relate to changes in the scope of sell-side analyst activity over time (aggregate number of analysts, number of reports, etc.). Perhaps more importantly, we know little about whether changes in the scope of the sell-side analyst industry impact the overall information environment and have consequences for market participants. Evidence on analyst activity from an aggregate perspective can provide important insights into the nature of competition among analysts and can shed light on questions that cannot be addressed simply by examining analysts' activities at the firm level.

This study attempts to fill the above gap in the literature. Specifically, we examine how the scope of the sell-side analyst industry evolves over time and how it varies with different economic factors. We find that changes in the scope of the sell-side analyst industry have economic consequences for market participants. Our findings suggest that a larger sell-side analyst industry encourages more intensive competition that increases the quality and informativeness of analysts' reports. Importantly, our results suggest that changes in the scope of the sell-side analyst industry produce spillover effects that relate to the unique way in which analysts compete with each other within industries, as opposed to within firms.

Studying the scope of the sell-side analyst industry provides insights beyond studying analysts at the firm level. Specifically, only when we examine analysts at the level of the industries they cover (as opposed to the firms they cover) can we study the spillover effects of competition. While firm-level studies show that analyst competition (as measured by the number of analysts following a firm) positively affects the quality of a firm's analyst reports (Hong and Kacperczyk (2010)), these studies miss an important factor that cannot be analyzed at the firm level alone: analyst competition at the industry level. For example, in a typical industry group, about 176 firms receive analyst coverage. While analysts compete with each other in terms of their coverage of these firms, they do not cover all of the firms in an industry. Typically, when an analyst leaves an industry, about 15 firms in that industry are directly affected by the loss of coverage. The spillover effect that we investigate, however, considers how the loss of coverage for this small set of firms affects the other 161 firms in the industry that are not directly affected by the analyst's departure.

There are good reasons to suspect that industry-level competition is important. Analysts compete at the industry level for II rankings and industry prestige (Stickel (1992), Hong and Kubik (2003), Ljungqvist et al. (2007), Groysberg, Healy, and Maber (2011)). Given that industry ranking selections and prestigious job positions are limited, competition among analysts for these accolades should increase as the number of analysts in an industry increases. Industry-level competition is also unique because it arises even when analysts do not cover the same firms. This difference allows us to examine the spillover effects of changes in the scope of the sell-side analyst industry. We hypothesize that the spillover effects resulting from a loss of analyst coverage for a subset of firms ultimately affects the quality of research produced in an entire industry along dimensions such as aggregate forecast quality and informativeness.

Because changes in the scope of the sell-side analyst industry (i.e., number of analysts employed, number of brokers, and number of firms receiving coverage) may have important economic consequences, we begin our analyses by examining the extent of these changes over time. Our data suggest that the number of analysts has grown moderately over the 1990 to 2010 period and exhibits differential growth patterns based on brokerage size.[1] Over the past decade, larger brokerage houses have employed a smaller portion of the overall analyst population while smaller brokerage houses have substantially increased their analyst presence. We also examine how the scope of the analyst industry varies with economic factors including industry performance, investment banking activity, trading commissions, regulatory change, and technological change. Our analyses suggest that the total number of analysts in an industry varies positively with industry initial public offering (IPO) activity and changes in trading volume. Our results also suggest differential sensitivity of analyst industry scope based on brokerage house size, with the largest brokerage houses being most sensitive to IPO activity—a key component of their business services. Overall, our evidence suggests that changes in the number of analysts covering an industry are related to changes in economic conditions and regulation.

We next consider the main questions of interest in this paper, namely, whether changes in the scope of the sell-side analyst industry have economic consequences and whether the effects of these changes at the industry level are distinct from those at the firm level. We propose that one channel through which industry-level changes in analysts' scope can have spillover effects on the quality of analyst research is through changes in industry-level competition. Increased competition at the covered industry level can potentially enhance the quality of analyst reports within an industry by increasing analyst effort and in turn information quality. As analyst industry competition increases, analysts try to distinguish themselves from other analysts by increasing their effort in order to produce higher quality research for all stocks in their portfolio. This increased effort can lead to greater information for other analysts in the industry because analysts often use the reports of their industry peers to construct their own reports (Clement, Hales, and Xue (2011)). If increased competition positively affects the quality of some analysts' reports, these reports can in turn affect the quality of other reports as well as the informativeness of market prices (Grossman and Stiglitz (1980)). In addition, if new analysts

[1] The growth in the sell-side analyst industry is significantly smaller than that for other finance professionals during this period (Greenwood and Scharfstein (2013)), suggesting that the costs and benefits of sell-side analyst activities likely differ from those of other finance-related activities. Unlike investment bankers or traders, analysts are often a cost center, and attributing how much they contribute to the overall bank activity is difficult even with the best data. Further, the role and contribution of analysts has changed significantly over time. For example, the Global Settlement weakened the connection between analyst activities and investment banking revenue, and trading commissions have declined significantly in recent years. In addition, advances in technology and increased corporate disclosure requirements have lowered the cost of independent financial analysis.

enter the industry, the supply of available reports for existing analysts will also increase. Accordingly, we expect changes in analyst competition in an industry to affect the quality of analyst reports not only for the firms these analysts cover (e.g., Hong and Kacperczyk (2010)), but also for the firms in the industry they do not cover.

To test this prediction, we use the number of analysts covering an industry as a proxy for analyst industry competition. As the number of analysts in an industry increases, we expect competition between analysts to increase. To help mitigate endogeneity concerns, our empirical tests follow prior studies in finance (e.g., Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012), Derrien and Kecskés (2013)) and employ drops in the number of analysts covering an industry resulting from brokerage house mergers and closures as a plausibly exogenous shock to analyst competition.[2]

We begin this analysis by examining how these drops relate to industry variation in two important attributes of analyst reports: (i) aggregate earnings forecast accuracy and (ii) aggregate optimism bias. As we focus on the industry-level spillover effects of analyst competition, we examine how changes in the number of analysts in an industry affect the reports of firms that are not directly affected by firm-level changes in coverage. Specifically, we aggregate reports for firms where industry-level analyst coverage changes, but firm-level coverage does not. As such, we isolate the indirect effects and focus on the spillover effects of changes in analyst industry competition. These industry spillover effects are part of what separates analyst industry competition from firm-level competition and highlight the significance of industry competition as an important and distinct mechanism affecting analyst activities.

We find that decreases in the number of analysts covering an industry are associated with higher aggregate absolute forecast errors and greater optimism bias. A one-unit drop in the number of analysts in an industry results in a 1.0% increase in aggregate absolute forecast error and a 1.4% increase in aggregate optimism bias. Relative to the unconditional means of these dependent variables, these effects represent changes of about 2.6% and 5.5%, respectively. Overall, these results indicate that decreases in analyst competition adversely affect the overall quality of analyst reports. As we exclude direct firm-level effects from our tests, our results suggest that industry-level changes in analysts have spillover effects that extend beyond the effects documented in firm-level studies (e.g., Hong and Kacperczyk (2010)). Our findings support the notion that analyst industry competition is a distinct form of competition that affects the quality of information analysts provide to market participants.

Identifying variation in the effects of changes in the number of industry analysts can increase our understanding about sell-side analyst industry competition as a unique mechanism. In particular, changes in analyst industry competition should be more significant in settings where individual analysts affect

[2] While analyst drops provide a plausibly exogenous setting for examining the effects of changes in analyst presence, they are limited to the extent that they do not capture increases in analyst presence. In Section II.D, we consider all changes in analyst presence and find similar results.

competition to a greater extent. Indeed, we find that the effects of industry analyst changes are more pronounced in settings where drops in analysts are expected to affect competition. Specifically, the effects of analyst changes are less significant for industries with better information environments (i.e., greater analyst following) and for industries in which analysts can more easily forecast individual firms' earnings (i.e., higher earnings synchronicity), and are more significant when industry analyst drops relate to more knowledgeable analysts (i.e., All-Star analysts).

Further analysis suggests that the effects we document are related in part to analysts exerting less effort after losing influential peers. In the months following drops in analyst coverage, we find that the remaining analysts are less likely to cover new firms, issue fewer reports and forecasts, produce less timely reports, and ask less challenging questions on conference calls. We also show that drops in analyst coverage are associated with higher analyst forecast dispersion, consistent with a decrease in analyst information convergence. These findings support the prediction that drops in industry analyst coverage affect the quality of analyst reports through changes in competition. In addition, these findings (i.e., increased shirking and lower information convergence) extend those of studies that examine changes in analyst following at the firm level by providing new evidence about how analysts affect firms' information environments.

Prior studies show that analyst reports also have implications for valuation (e.g., Womack (1996), Asquith, Mikhail, and Au (2005), Bradley et al. (2014)). Accordingly, our next set of tests examines whether changes in industry analyst coverage affect price formation. If drops in industry analysts result in lower quality analyst reports, they could also have consequences for valuation. Lower quality reports lead to reports that have less information content and consequently should have less impact on market prices. In addition, if analyst reports have less information content, it is reasonable to predict that some corporate disclosures, such as earnings announcements, should be more informative because less of the information in these disclosures is preempted by analyst reports. Consistent with these predictions, we find that the information content of analyst reports in an industry is lower when an industry loses analysts (about 0.28% lower per analyst lost) while the information content of earnings announcements is higher (about 0.42% higher per analyst lost). Relative to the unconditional means of these dependent variables, these effects represent changes of about 2.0% and 3.3%, respectively. These results suggest that the reduction in forecast quality associated with decreasing the number of analysts in an industry also appears to decrease the flow of information, which slows the dissemination of information to market participants.

Our final analyses facilitate comparisons between changes in industry-level analyst competition and changes in firm-level competition. We extend the methodology of Hong and Kacperczyk (2010) and examine how changes in analyst presence at the industry and firm levels affect forecast bias as well as forecast accuracy, using both OLS regressions and difference-in-differences (DID) estimation analyses at the firm level. Consistent with industry competition having an important and distinct effect on analyst behavior, we find that industry drops are associated with reductions in forecast accuracy and increases in optimism bias. These effects are not only incremental to firm-level effects but are also economically meaningful.

Our study offers two important contributions to the literature. First, it is the first to our knowledge to explore the sell-side analyst industry from an aggregate perspective.[3] We provide evidence that, despite the unique nature of the sell-side analyst industry, changes in the scope of sell-side analyst activities are related to changes in economic conditions (e.g., IPO activity and trading volume) and regulation, and that these effects differ across brokerage houses. Moreover, our findings highlight the importance of industry competition in the sell-side analyst industry by demonstrating that a larger analyst presence in an industry can have important spillover effects for firms in the same industry, even though these firms did not experience a change in analyst coverage.

Second, we document spillover effects resulting from sell-side analyst industry competition. Prior studies consider analyst activities at the firm level, but a significant amount of analyst competition occurs at the industry level (e.g., II rankings). The industry spillover effects that we examine are likely the result of competitive pressure, as analysts compete more to provide more accurate, less biased, and more informative reports. Importantly, these industry spillover effects are incremental to firm-level effects examined in prior studies (e.g., Hong and Kacperczyk (2010)), suggesting that competition at the industry level has an important effect on analyst behavior that has been previously unexplored.

Our findings also have implications for regulators and practitioners, as they suggest that there are benefits associated with a larger, more competitive analyst industry. Regulation that aims to curb analyst incentives can thus have potentially unintended consequences if it limits the scope of sell-side analyst activities.

I. Changes in the Sell-Side Analyst Industry over Time

A. Data and Descriptive Statistics

Before examining the economic consequences of changes in the scope of the sell-side analyst industry, it is important to document the extent of such changes over time. We begin by examining how the sell-side analyst industry has evolved over time and whether these changes relate to variation in economic factors. While there are many potential measures of analyst activity, perhaps the most natural metric is the number of analysts actively producing research.

Analyst employment decisions at most brokerage houses are likely made continuously over time, rather than at the end of a quarter or year. Analysts

[3] Prior studies emphasize the importance of examining aggregate-level economic relationships in other contexts. While some firm-level effects (such as poor post-equity issuance returns) are observed at aggregate levels (e.g., Baker and Wurgler (2006)), others (such as postearnings announcement drift and the accrual anomaly) weaken or even reverse direction (e.g., Kothari, Lewellen, and Warner (2006), Hirshleifer, Hou, and Teoh (2009)).

typically provide reports at frequent intervals, often monthly or more frequently. In addition, monthly analyst reports reflect an important horizon for equity analysts as monthly consensus forecasts are an important earnings metric. To account for these issues, we calculate changes in analysts on a monthly basis. To identify active analysts, we track all entry and exit into the analyst industry based on I/B/E/S data. We define an entering analyst as any analyst issuing her first forecast in the sample, or an analyst who issues a forecast after not doing so for a period of at least 12 months. Similarly, we define an existing analyst as any analyst issuing her last forecast in the sample, or who does not issue a forecast in the next 12 months. Changes in analysts are computed as the difference between entering and exiting analysts, and the total number of analysts employed at any given time is simply the running total based on these changes and the prior level.

To compute our analyst measures, we obtain data from nearly 12.3 million analyst reports available on I/B/E/S between 1990 and 2010 with sufficient data to identify brokerage houses, analysts' identity, and industry coverage.[4] We do not consider data prior to 1990 because of concerns regarding sparse analyst coverage on I/B/E/S in earlier years (Hong, Lim, and Stein (2000), Diether, Malloy, and Scherbina (2002)). In addition to examining the number of analysts in the industry, we also use the number of brokers (using a similar method) and the total number of firms receiving coverage as proxies for the scope of the industry. These data are summarized in Figure 1, which plots the growth in the sell-side analyst industry over the past 20 years based on the number of analysts providing reports (Panel A), the number of brokers employing analysts (Panel B), the number of firms receiving coverage in the market (Panel C), and the number of analysts employed by brokerage size (Panel D). This figure highlights several interesting trends.

Panel A shows that the number of analysts employed in the sell-side analyst industry has been generally increasing over the past two decades.[5] Throughout the 1990s, the total number of analysts rose steadily from a starting population of around 2,000 to a peak of 3,226 by the end of 1999. In the 2000s, the number of analysts remained relatively steady, ranging between 2,700 and 3,200 analysts. It is also important to note that these trends do not appear to be driven by changes in how brokerage houses report to I/B/E/S over time, as we see similar trends using the number of analysts from a constant sample of 36 brokers who report to I/B/E/S over the entire sample period. We also note similar trends in

[4] Our sample does not include estimates from some brokers, notably Lehman Brothers and Merrill Lynch, because these data are not available on I/B/E/S in recent years. Thus, our sample understates the overall number of analysts.

[5] It is important to note that this figure only includes the lead analyst on the research team and does not include associates or junior analysts (Jegadeesh et al. (2004)). When an analyst name is available on the Broker Translation file, these codes generally map to the lead analyst's name, but sometimes they refer to pairs of analysts or the name of the team (e.g., sector). In the Internet Appendix, we find that our inferences are unchanged if we remove observations with names that refer to analyst pairs or sectors. The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

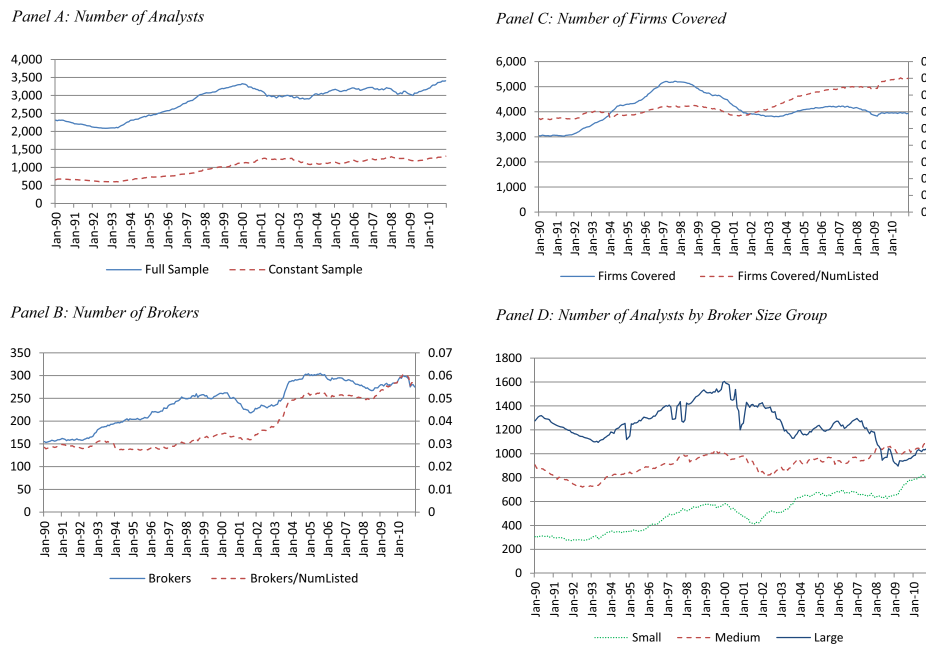

Figure 1. Time series plot of analyst activity (1990 to 2010). This figure provides time series plots of analyst activity as reported in I/B/E/S each month between 1990 and 2010. Panel A plots the number of analysts. The solid line corresponds to the full sample while the dashed line corresponds to a constant sample of brokers with reports every month throughout the sample period. Panel B plots the number of I/B/E/S brokers. The solid line (left axis) corresponds to the number of brokers and the dashed line (right axis) corresponds to the number of brokers scaled by the number of listed firms, as reported by CRSP. Panel C plots the number of firms covered by I/B/E/S. The solid line (left axis) corresponds to the number of firms and the dashed line (right axis) corresponds to the number of firms scaled by the number of listed firms, as reported by CRSP. Panel D plots subsets of brokers based on size. On average, small brokers have fewer than 10 analysts over the sample period, medium brokers have 10 to 30 analysts over the sample period, and larger brokers have more than 30 analysts over the sample period. (Color figure can be viewed at wileyonlinelibrary.com)

the growth of sell-side analyst activity in the plots of the number of brokers and number of firms receiving coverage. Panel B shows that the number of brokers rises from less than 150 in 1990 to nearly 300 by the end of the sample period. Similarly, Panel C shows a gradual increase in the percentage of listed firms covered by analysts over time.

Recent business press articles suggest that the number of analysts at prominent brokerage houses has declined in recent years as these houses have restructured their research business to adapt to the changing economic environment.[6] However, the trend in Figure 1, Panel A, suggests that the number of analysts increased with the recent market recovery. To investigate this discrepancy, we further examine trends in the number of analysts by brokerage size.

[6] See Papina (2009) and Segal (2010).

Panel D provides evidence that trends in the number of analysts employed by brokerage houses of different size are similar to those of the overall population. One interesting exception is that the number of analysts employed at large brokerages is decreasing in recent years consistent with business press stories. This trend is reversed for smaller brokerages.[7] These results are consistent with recent changes in the analyst industry in terms of the growth of smaller, independent research firms.

The panels in Figure 1 suggest that changes in the number of analysts relate to economic factors. Declines in analyst activity appear around market downturns, particularly around the recession of the early 1990s, the burst of the dot-com bubble in 2001, and the recent global financial crisis in 2007 to 2008, consistent with analysts' presence declining when their services are likely to be less profitable. Similarly, the number of analysts increased during the market rise in the late 1990s and after the financial crisis. These findings are consistent with anecdotal evidence that research budgets are slashed during economic downturns.[8]

While market-level plots offer interesting insights into changes in the sell-side analyst industry, they do not reflect how analysts organize themselves. More often than not, analysts tend to specialize in particular industry groups based on the firms they cover. Thus, a formal examination of the sell-side analyst industry is best conducted at the industry level, as this most accurately reflects how analysts organize themselves. Prior research suggests that the Global Industry Classification Standard (GICS) provides the most accurate representation of how many brokerage houses organize their analyst teams (Bhojraj, Lee, and Oler (2003), Boni and Womack (2006), Kadan et al. (2012)). Accordingly, we use GICS to classify analysts into industries based on whether they provide any coverage for firms in these industry groups.

The GICS taxonomy consists of 10 sectors, 24 industry groups, 68 industries, and 154 subindustries.[9] We aggregate our variables across GICS industry groups rather than at the broader sector level or the more detailed industry or subindustry level because industry groups provide the most consistent level of classification across brokerage houses. While larger brokers have sufficient resources to employ analysts at a finer level of coverage detail, smaller brokers are constrained in their coverage decisions and staff at a coarser level. We find substantial variation in brokerage house size, with some brokers employing as

[7] This overall trend is also consistent with estimates of the U.S. Department of Labor, which expects employment of financial analysts to grow 23% in the next 10 years due to increasing demand for understanding complex financial products. See http://www.bls.gov/ooh/business-and-financial/financial-nalysts.htm#tab-6.

[8] See http://www.economist.com/news/finance-and-economics/21594358-bear-market-or-bull-analysts-give-bad-advice-consistently-wrong. This information is provided by Frost Consulting, who claims that in the most recent crisis research budgets were cut by 40%.

[9] Prior to 2003, there were only 23 GICS Industry Groups. In April 2003, GICS introduced an additional industry group for Semiconductors & Semiconductor Equipment (i.e., 4530) and reclassified some of the firms previously included in GICS Industry Group 4520. We drop observations for these two industry groups between 2002Q4 and 2003Q2 to allow for the reclassification of analysts and firms in our sample.

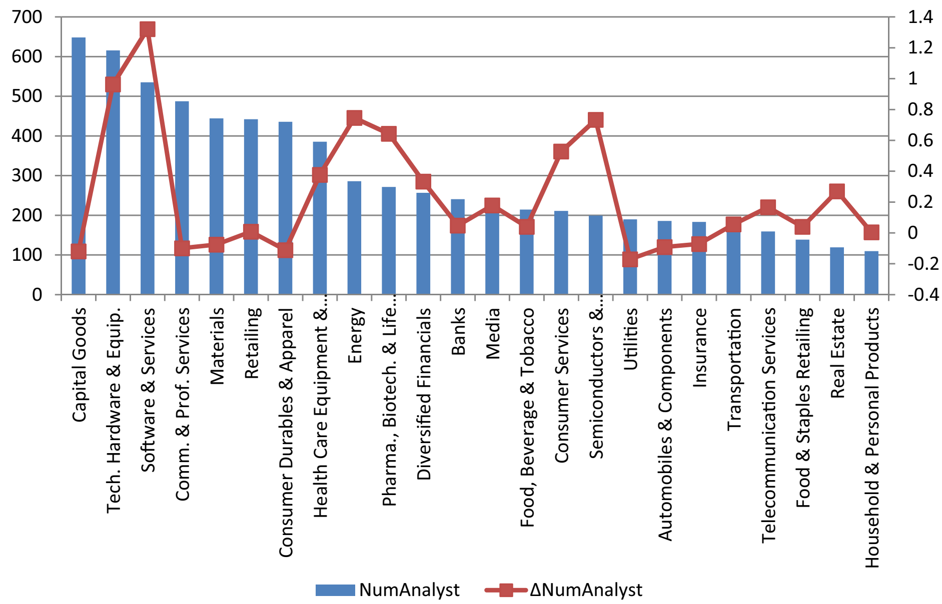

Figure 2. Number of analysts by GICS Industry Group (1990 to 2010). This figure displays the average number of analysts (left axis) and average monthly changes in analysts (right axis) from 1990 to 2010 across 24 GICS industry groups. (Color figure can be viewed at wileyonlinelibrary.com)

few as 3 analysts and others employing over 100 analysts. Additionally, Kadan et al. (2012) are unable to find any broker that provides consistent coverage across all 68 GICS industries over time. GICS industry groups provide the best choice in terms of understanding the way in which analysts organize themselves (i.e., GICS) as well as the precision (i.e., level of aggregation) with which analysts aggregate.

Figure 2 depicts the variation in the level and changes in analyst coverage across the industries in our sample. Industry groups in the industrial sectors, such as capital goods (e.g., Boeing Co., Honeywell Inc., etc.) and commercial and professional services (e.g., H&R Block, Weight Watchers International Inc., etc.), attract large numbers of analysts but are also relatively steady over time (i.e., little change in the number of analysts). Not surprisingly, industries in the information technology sector, such as software and services and semiconductors, have exhibited the largest growth in the past two decades, adding on average one new analyst per month.

B. The Relation between Sell-Side Analyst Industry Scope and Economic Factors

Standard economic analysis suggests that analyst presence should depend on the marginal value that analysts bring to the brokers that employ them. While the value of various finance-related activities (e.g., underwriting, trading gains, etc.) can be measured based on outputs, the marginal contribution of research analysts to brokerage houses' bottom line is difficult to measure—even within brokerage houses, let alone for outside observers. Given these limitations, we consider how variations in economic factors (discussed in more detail below) that potentially influence brokerage house profitability relate to the scope of the analyst industry.

While changes in the financial sector in general are expected to relate to changes in economic factors (e.g., Greenwood and Scharfstein (2013)), it is not clear whether this should be the case for sell-side analysts. Unlike investment bankers, traders, and other finance professionals, analysts are generally considered cost centers as opposed to profit centers for their employers. Most analysts do not bring direct revenue to their employers, but instead bring indirect revenues through investment banking or brokerage revenue streams. This suggests that the returns to brokerage houses from additional spending on analyst activities are likely to be more uncertain and possibly lower than those of other activities. In addition, it is likely that the role and contribution of analysts in capital markets has changed significantly over the sample period. The Global Settlement weakened the connection between analyst activities and investment banking revenue. Furthermore, advances in technology combined with increases in public disclosure requirements have significantly lowered the cost of financial analysis for other capital market participants. For example, Table I of Greenwood and Scharfstein (2013) suggests that total securities outputs (e.g., fees from asset management, underwriting, and other brokerage services) grew by over 200% from 1997 to 2007, while Figure 1, Panel A, in this paper shows that the number of analysts in the industry grew by only about 13% over the same period. Thus, given the nature of analyst activities and the likelihood that the relation of the analyst industry to economic factors has been changing over time, it is useful to analyze the sell-side analyst industry and the factors related to changes in its scope.

We employ several proxies for analyst profitability. First, we consider proxies related to analyst profitability through market growth. We use industry returns, as we expect analyst activity to become more profitable during periods of market growth. Similarly, we use the change in the number of listed firms, which we expect to relate positively to changes in analyst activity as it captures both demand for analyst services as well as the commissions that can be earned from cross-subsidizing research activities with underwriting revenues (Chen and Ritter (2000)). In our tests, we decompose the change in the number of listed firms into IPOs and net delistings to better isolate the cross-subsidization effect from brokerage activities. We also expect growth in overall industry trading volume to be positively associated with analyst activity because analyst compensation is often related to trading commissions (Ljungqvist et al. (2007)). Second, we consider aggregate factors including the change in the overall profitability of the investment banking industry (Δ*Broker Income*) as well as the change in macroeconomic conditions based on the CFNAI index.

Table I

Economic Factors Associated with Changes in Analyst Scope

This table reports results from regressions of monthly changes in analyst scope on proxies for analyst-related profit and analyst information advantage. Panel A provides OLS regressions of changes of analysts ($\Delta Analysts_{t+1}$) as the measure of analyst scope based on the groupings from Figure 1. All regression results are based on monthly measures of analyst scope and proxies for analyst-related profits and information advantage across 24 GICS industry groups from 1990 to 2010. Proxies for analyst-related profit and information advantage are defined in Appendix A. Standard errors are clustered by industry and month. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Regressions of ΔAnalysts

	All Brokers (1)	Small Brokers (2)	Medium Brokers (3)	Large Brokers (4)
Returns	3.0128	1.2559	1.7534	0.0035
	(1.44)	(1.63)	(1.62)	(0.00)
Number of IPOs	0.3866***	0.0712***	0.1269***	0.1885***
	(6.46)	(3.02)	(5.48)	(7.57)
Net Delistings	−0.0514	−0.0132	−0.0186	−0.0197
	(−1.33)	(−1.05)	(−1.55)	(−1.32)
ΔTrading Volume	0.0104***	0.0051***	0.0027***	0.0026***
	(12.20)	(3.84)	(3.07)	(4.23)
ΔVolatility	−15.2843	−6.3277	−5.1200	−3.8365
	(−0.70)	(−0.69)	(−0.56)	(−0.32)
ΔBroker Profits	0.2221	0.0855	−0.0029	0.1396*
	(1.61)	(1.59)	(−0.09)	(1.86)
ΔCFNAI	−0.0414	0.0541	−0.0820	−0.0135
	(−0.27)	(0.93)	(−1.40)	(−0.16)
Reg FD	−2.7319***	−1.0914***	−0.6503**	−0.9902**
	(−3.17)	(−3.68)	(−2.36)	(−2.45)
Global Settlement	0.0486	0.3961***	0.0352	−0.3828
	(0.09)	(2.96)	(0.29)	(−0.93)
SOX	−0.8383	−0.1241	0.4427**	−1.1569**
	(−1.15)	(−0.58)	(2.43)	(−2.38)
Financial Crisis	−0.4773	−0.2454	0.0657	−0.2976
	(−0.77)	(−1.26)	(0.41)	(−0.82)
ΔCost per MB	0.0000	−0.0000	0.0000	0.0000
	(0.72)	(−0.03)	(1.37)	(0.41)
ΔInst. Holdings	0.0051	−0.0002	0.0008	0.0045***
	(1.53)	(−0.17)	(0.25)	(2.74)
ΔNet Insider Trading	2.0081	0.8401	0.2470	0.9211
	(1.10)	(0.95)	(0.24)	(0.70)
ΔShort Interest	−4.6459	0.1811	−3.3100	−1.5169
	(−0.70)	(0.05)	(−1.08)	(−0.42)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,877	5,877	5,877	5,877
R^2	0.11	0.05	0.06	0.08

Panel B: Regressions of Other Measures of Analyst Scope

	$\frac{\Delta \text{Analyst}}{\text{Analyst}}$ (1)	$\frac{\Delta \text{Analyst}}{\text{MVAL}}$ (2)	$\frac{\Delta \text{Analyst}}{\text{\#ListFirms}}$ (3)	$\frac{\Delta \text{Analyst}}{\text{\#CovFirm}}$ (4)	ΔBrokers (5)	ΔFirmCov (6)	$\frac{\Delta \text{FirmCov}}{\text{\#ListFirms}}$ (7)
Returns	1.5017*	1.6575	1.8537	3.2414*	2.2698***	1.1321	0.3681
	(1.81)	(1.34)	(1.51)	(1.69)	(2.70)	(0.82)	(0.75)
Number of IPOs	0.0687***	0.0819***	0.0639***	0.1062***	0.0131	0.6314***	0.1329***
	(9.15)	(4.51)	(6.60)	(7.05)	(1.12)	(23.20)	(6.76)

(*Continued*)

Table I—*Continued*

Panel B: Regressions of Other Measures of Analyst Scope

	ΔAnalyst / Analyst (1)	ΔAnalyst / MVAL (2)	ΔAnalyst / #ListFirms (3)	ΔAnalyst / #CovFirm (4)	ΔBrokers (5)	ΔFirmCov (6)	ΔFirmCov / #ListFirms (7)
Net Delistings	−0.0126	−0.0114	−0.0125	−0.0199	−0.0165**	−0.1017***	−0.0208**
	(−1.47)	(−1.39)	(−1.46)	(−1.47)	(−2.13)	(−3.70)	(−2.34)
ΔTrading Volume	0.0023***	0.0023***	0.0024***	0.0034***	0.0028	−0.0002	−0.0002
	(4.82)	(3.17)	(4.90)	(4.95)	(1.21)	(−0.28)	(−0.42)
ΔVolatility	0.0953	−1.7103	−0.0455	−3.7375	1.4332	0.6800	2.4893
	(0.01)	(−0.19)	(−0.01)	(−0.28)	(0.18)	(0.05)	(0.54)
ΔBroker Income	0.0844*	0.0463	0.1227	0.1640	0.0746	0.1236	0.0583
	(1.67)	(0.78)	(1.57)	(1.54)	(1.36)	(1.43)	(1.64)
ΔCFNAI	−0.0288	0.0377	−0.0674	−0.0709	0.0190	−0.0212	−0.0028
	(−0.52)	(0.50)	(−0.82)	(−0.58)	(0.26)	(−0.19)	(−0.07)
Reg FD	−0.8191***	−0.6264***	−0.9917***	−1.6830***	−1.1663***	−1.6030***	−0.4852***
	(−4.16)	(−3.87)	(−4.35)	(−4.27)	(−5.40)	(−2.61)	(−3.95)
Global Settlement	0.0746	0.0107	−0.0909	−0.1530	0.3780**	−0.1142	−0.0789
	(0.42)	(0.07)	(−0.56)	(−0.54)	(2.50)	(−0.41)	(−0.79)
SOX	−0.1686	−0.2006	−0.2757	−0.4629	0.5499***	−0.0889	−0.1121
	(−0.75)	(−0.85)	(−1.00)	(−0.93)	(3.10)	(−0.24)	(−0.75)
Financial Crisis	−0.2071	−0.0944	−0.2292	−0.2671	−0.0160	−0.1917	−0.1822
	(−0.93)	(−0.54)	(−0.65)	(−0.56)	(−0.08)	(−0.63)	(−1.44)
ΔCost per MB	0.0000	0.0000	0.0000	0.0000	0.0000	−0.0000	0.0000
	(1.03)	(0.86)	(0.97)	(0.82)	(0.92)	(−0.81)	(0.01)
ΔInst. Holdings	−0.0001	−0.0016	−0.0005	−0.0015	0.0010	0.0027	−0.0000
	(−0.06)	(−0.99)	(−0.36)	(−0.69)	(0.82)	(0.66)	(−0.03)
ΔNet Insider Trading	1.7040**	1.2916*	3.5448***	5.6807***	1.2768	−0.4590	0.5905
	(2.30)	(1.94)	(2.77)	(3.08)	(0.98)	(−0.38)	(0.81)
ΔShort Interest	−2.7804	−0.4467	−3.7388	−5.6206	−5.8700***	2.4724	2.1450
	(−1.43)	(−0.16)	(−1.29)	(−1.32)	(−2.71)	(0.83)	(1.30)
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,877	5,877	5,877	5,877	5,877	5,877	5,877
R^2	0.08	0.03	0.06	0.05	0.06	0.23	0.11

Because we expect analyst activities to be more valuable when analysts have an information advantage vis-à-vis other market participants, we also include indicator variables to capture periods related to the enactment of Reg FD, the Global Settlement, and the passage of the Sarbanes-Oxley Act. While each of these events is potentially confounded with other contemporaneous events, we expect the circumstances surrounding these events to reduce the value of analyst services because they decrease analysts' private information and raise questions about the credibility of analyst reports (Bailey et al. (2003)). We also include an indicator for the recent financial crisis as it represents a time during which analyst services potentially became more useful to investors (Loh and Stulz (2014)). To further examine analysts' information advantage as well as the demand for their reports, we include the change in industry net insider trading activity and the change in industry short interest, as these activities can potentially crowd out analysts' information advantage (Bushman, Piotroski, and Smith (2005)). Similarly, we consider return volatility in our analysis. While volatility is frequently associated with poor market performance, it can also relate to increased uncertainty, which can create higher demand for analyst reports (Loh and Stulz (2014)). We further consider the change in the level of institutional holdings, as buy-side investors may demand sell-side services, and the change in the cost per megabyte of computing power over time, to capture changes in the cost of information processing related to the demand for outsourcing research analysis (Hauswald and Marquez (2003)). Finally, we include industry and calendar month fixed effects. All variable definitions are provided in Appendix A.

Since the dependent variable of this analysis, the change in the number of analysts covering an industry, is computed monthly, we also measure the independent variables on a monthly basis with a lag. Given the competitive nature of capital markets, we expect the sell-side analyst industry to respond relatively quickly to significant economic changes. Using monthly data helps us to more closely link the independent variables to the dependent variables, which limits the inclusion of stale information from our analysis.[10]

Table I reports the results of regressing the change in the number of analysts by industry on proxies for analyst profitability. Column (1) provides the results for the full sample (i.e., all brokerage houses). Several interesting findings emerged. Changes in the number of analysts are positively and significantly related to *Number of IPOs* and Δ*Trading Volume*, consistent with these proxies reflecting greater demand for analyst services. In terms of economic significance, a one-standard-deviation increase in *Number of IPOs* in an industry results in about one new analyst per industry-month, whereas a one-standard-deviation increase in Δ*Trading Volume* results in about 0.14 more analysts.[11] Changes in the number of analysts are also negatively related to the passage of Reg FD, consistent with this regulation decreasing analysts' private information advantage. The months following Reg FD are associated with monthly decreases of 2.73 analysts on average.[12] In univariate analyses reported in the Internet Appendix, we also find positive and significant associations between changes in the number of analysts and *Returns*, Δ*Broker Income*, and Δ*Inst. Holdings*.

[10] We acknowledge that our analyses may not incorporate all changes in economic activity. First, the speed of these changes may vary across brokerage houses and industries. Further, labor markets are sometimes sticky, despite the competitive nature of capital markets. However, many of our variables have significant time series correlation and thus likely capture more than just the activity of a single month. Including additional lagged independent variables is therefore likely to produce results that are difficult to interpret due to multicollinearity (Greene (2003)). Rather than applying the assumptions of a distributed lag model to our analyses, we conduct robustness tests using rolling quarterly independent variables as well as a completely quarterly analysis. As the general tenor of our inferences remains unchanged based on these tests, we report only the monthly analyses.

[11] These estimates are based on the following sample standard deviations: *Number of IPOs*: $\sigma =$ 2.39 and Δ*Trading Volume*: $\sigma =$13.60.

[12] In the Internet Appendix, we also conduct the levels regressions at the industry level and obtain similar inferences. While not significant in changes, the extent of insider trading loads negative and significant in a levels regression. The results are also similar when defining the number of IPOs and delistings as a percentage of firms in the industry.

We further examine changes in the number of analysts for different subsets of brokers based on the grouping in Figure 1, Panel D. In columns (2) to (4) of Table I, we remeasure changes in the number of analysts at the industry level based on the average brokerage size over our sample period. This analysis reveals several important findings. First, consistent with the graphical evidence provided in Panel D of Figure 1, we confirm that the period surrounding Global Settlement had a significant impact on the smallest brokerage houses, as the coefficient on the indicator variable for this period is positive and significant. Second, the sensitivity of analyst activities to aggregate IPO activity varies monotonically based on the size of the brokerage house. The smallest brokerage houses are the least sensitive to IPO activity (coefficient = 0.0712), while the medium-sized and largest brokerage houses are more sensitive to IPO activity (coefficients = 0.1269 and 0.1885, respectively). Third, sensitivity to changes in trading volume follows the opposite pattern, with coefficients declining monotonically from the smallest brokerage house to the largest brokerage house. Overall, these findings are consistent with prior work related to individual analysts' careers (e.g., Hong and Kubik (2003), Groysberg, Healy, and Maber (2011)) and suggest that the profitability of analyst services varies based on brokerage houses. Smaller brokerage houses appear to be more likely to fund analyst research from trading profits, whereas the largest brokerage houses depend more heavily on investment banking activity generated through IPOs.

In Panel B, we reexamine the full sample results using alternative measures of analyst activity including different scalars (columns (1) to (4)), changes in brokers (column (5)), and changes in firms covered (columns (6) and (7)). We first note that our above inferences are generally not affected by scaling Δ*Analyst* by industry characteristics. Scaling Δ*Analyst* by the number of analysts, market value, and the number of listed or covered firms within an industry (columns (1) to (4)) produces similar results. Further, *Number of IPOs* and Δ*Trading Volume* are positively and significantly correlated with analyst activity in most cases. Similarly, the passage of Reg FD is associated with a general decline in analyst activity. We also find that changes in the number of brokers are positively related to *Returns* and negatively related to delistings, and changes in the number of firms covered are positively associated with *Number of IPOs* and negatively related to delistings.

Overall, the evidence in this section documents significant changes in the scope of the sell-side analyst industry over time and suggests that these changes appear to be related to economic factors associated with analysts' profitability. Specifically, we find that these changes relate positively to the number of IPOs and trading volume, but that these findings vary based on brokerage type. While the list of economic factors we examine is by no means exhaustive, our findings provide some initial insights regarding the growth of the sell-side analyst industry and shed important light on the uniqueness of this industry compared to other financial services industries.

II. Economic Consequences of Changes in the Sell-Side Analyst Industry

Do changes in the scope of the sell-side analyst industry, such as those documented in Section II, have real consequences for market participants? That is, do changes in aggregate analyst presence affect the quality and informativeness of analyst reports in an industry? While other finance-related market participants affect market prices directly through their trading activities in various financial instruments (Adrian, Etula, and Muir (2014), Philippon (2015)), sell-side analysts seek to influence market participants by providing information. This information intermediary role, however, is potentially limited by changes in regulation (Bailey et al. (2003)), decreases in the costs of information technology (Hauswald and Marquez (2003)), and a general trend toward greater price efficiency (Bai, Philippon, and Savov (2015)).

Theory suggests that changes in competition impact how economic agents acquire and supply information (e.g., Grossman and Stiglitz (1980), Admati and Pfleiderer (1988), Besley and Prat (2006), Gentzkow and Shapiro (2006), Hauswald and Marquez (2006)). Much of the external and internal evaluation of sell-side analysts is done at the industry level. For example, the industry ranking battle in the sell-side analyst industry is considered highly competitive. Analysts compete for a limited number of prominent positions in top investment banks, institutional clients evaluate analysts relative to their industry peers, and analysts compete with one another for prestigious industry rankings and influence (Mikhail, Walther, and Willis (1999), Hong and Kubik (2003), Ljungqvist et al. (2007)). In fact, analyst competition between their peers at the industry level is one of most significant factors that determine analysts' future career progression and compensation (Stickel (1992), Groysberg, Healy, and Maber (2011)). Furthermore, intense rivalry among peers can have important effects on how individuals compete with each other (Kilduff, Elfenbein, and Staw (2010)), and we expect this behavior to strongly apply to analysts (Reingold (2006)).

One important aspect of competition at the industry level is that its effects extend to analysts' activities throughout the entire industry. In other words, the way analysts compete with their industry peers extends beyond their coverage of a common set of individual firms (as in Hong and Kacperczyk (2010), for example) to also affect their coverage of other firms in the industry that have less overlap in coverage. Increased competition at the industry level can have spillover effects that potentially enhance the quality of analyst reports within an industry by increasing analyst effort and consequently information quality.

As analyst competition in an industry increases, analysts increase their efforts to produce higher quality research for all stocks in their portfolios to distinguish themselves from other analysts in the industry. Prior studies demonstrate that high quality reports are a function, in part, of effort, so increased effort should result in higher quality reports, on average (Clement (1999), Jacob, Lys, and Neale (1999)). Analyst competition also serves as a disciplining mechanism to temper analysts' incentives to be overly optimistic (Ljungqvist, Marston, and Wilhelm (2006), Hong and Kacperczyk (2010), Fong et al. (2014)). For example, prior studies suggest that analysts often issue optimistic reports because positive reports promote higher investment banking revenue and trading commissions (e.g., Michaely and Womack (1999)). Further, analysts may have a natural disposition toward issuing optimistic reports because they anchor their forecasts on firms' plans for future success rather than on past results (Kahneman and Lovallo (1993)). Ljungqvist et al. (2007) find that competition for II approval can help discipline this optimism as it leads analysts to provide reports that are more accurate and less optimistically biased. Accordingly, we expect competition among analysts at the industry level to have significant spillover effects on the quality of analyst reports in an industry, given the importance of their career incentives at this level (e.g., II rankings and industry prestige).

The increased effort associated with increases in analyst competition can lead in turn to greater information for other analysts in the industry. Unlike the output of other finance professionals (e.g., investment bankers' pitch books or buy-side reports), sell-side analyst reports are generally not proprietary, which allows analysts to use peers' analyst reports in constructing their own reports (Clement, Hales, and Xue (2011)).[13] If increased competition positively affects the quality of some analysts' reports, these reports can in turn affect the quality of other reports by providing more information for other analysts in the industry and by improving price informativeness (Grossman and Stiglitz (1980)). Thus, in addition to the effect on firms that directly experience a change in analyst coverage, industry competition can have a spillover effect on the quality of information provided by analysts for other firms in the same industry.

Prior studies examine the effects of analyst competition based on the number of analysts covering a firm (e.g., Hong and Kacperczyk (2010)). This measure is closely related to analysts' institutional environment because, as the number of analysts increases, there is more competitive pressure to provide higher quality reports. To examine whether industry-level analyst competition has effects beyond firm-level competition, we employ a similar measure based on the number of analysts covering an industry. This measure is particularly relevant in the analyst setting because analysts compete against their industry peers for a limited number of positions at investment banks and II rankings. Further, this measure is related to Hong and Kacperczyk's (2010) measure of competition and is consistent with studies in information economics that examine how competition and information production relate to the number of informed agents in the market (Grossman and Stiglitz (1980), Admati and Pfleiderer (1988)). Similar to prior analyst literature and other labor market settings (e.g., Holzer, Katz,

[13] Adrian, Etula, and Muir (2014) provide evidence that securities brokers' leverage explains the cross-section of asset returns, suggesting that financial intermediaries have a significant effect on market prices. Bai, Philippon, and Savov (2015) find that financial markets have become more informative over the past 50 years. Our study identifies analyst coverage as one specific mechanism through which prices can become more informative. We examine measures of market informativeness in Section II.E.

and Krueger (1991), Moen (1999)), we expect that, as the number of analysts in an industry increases, competition between analysts increases.[14]

It is useful to note that sell-side analysts typically cover many firms (in our sample the average number of firms per analyst in various industries ranges from 11 to 19 firms per analyst), and thus when an industry loses one analyst it loses some information on a group of firms. This observation distinguishes our study from those that examine firm-level analyst competition. Firm-level studies consider the effect of one firm losing an analyst on the other analysts covering that firm. In contrast, we examine the aggregate industry spillover effects of many firms in an industry losing an analyst on the analyst reports of the other firms in the industry that were not directly affected by this change.

For example, Eric Zimits, an analyst for Chase H&Q, covered about 17 firms in the communications sector, including Portal Software. He left the industry after the merger of Chase and JP Morgan in 2000 and as a consequence stopped covering these 17 firms. In reference to this example, previous studies examine how Mr. Zimits's drop in coverage of one firm (e.g., Portal Software) affects the analyst bias (Hong and Kacperczyk (2010)), liquidity (Kelly and Ljungqvist (2012)), or investments (Derrien and Kecskés (2013)) of Portal Software. In the current study, however, we examine how Mr. Zimits's drop of coverage for these 17 firms affects the analysts covering the other firms in the industry he did not cover. For example, Yumi Koh, a peer of Mr. Zimits's employed at Morgan Stanley around the same time, also covered firms in the communications sector, including Portal Software. However, Mr. Koh also covered some firms in this sector that were not covered by Mr. Zimits, such as Convergys Corp and CSG Systems. In reference to this example, our study examines how Mr. Zimits's drop affects the quality of reports that Mr. Koh and other analysts provide for firms such as Convergys Corp. and CSG Systems that Mr. Zimits did not cover. Mr. Zimits's departure provides incentives for other analysts in the industry (such as Mr. Koh) to be more biased and less accurate for all of the firms they cover because they face less competition and have less common information available. This spillover effect is distinct from the firm-level effect and aggregates indirect effects for other firms not directly affected by the drop in coverage but connected through a common industry group.

We begin our analysis by examining how changes in the number of analysts in an industry relate to the quality of analyst reports in that industry. We first consider two important attributes of analyst research reports as proxies for

[14] Some labor economics models assume that all workers are identical, suggesting that each worker contributes equally to the degree of competition. It is likely, however, that there is variation in terms of how analysts affect competition based on individual and industry characteristics. For example, in the industrial organizations literature, some studies measure firm competition based on the number of firms (e.g., Morrison and Winston (1990), Nickell (1996)), while others weight firms differently based on their market share (e.g., Herfindahl Index). We explore heterogeneity in our competition measures later in the paper through a series of cross-sectional analyses, similar to prior work on analyst competition at the firm level. Also, we note that our inferences are similar when we use the number of firms covered as our measure of competition.

report quality: (i) aggregate forecast earnings accuracy and (ii) bias. As we are specifically interested in the industry-level effects of analyst competition, we examine how changes in the number of analysts in an industry affect these attributes for the reports of firms that are not directly affected by firm-level changes in coverage. Specifically, we aggregate reports for firms within an industry where industry-level analyst coverage changes but firm-level coverage does not. As such, we isolate the spillover effects of changes in analyst industry competition. These industry spillover effects are part of what separates industry competition from firm-level competition (e.g., Hong and Kacperczyk (2010)) and highlight the significance of industry competition as a distinct mechanism affecting analyst activities.

We next explore variation in the impact of changes in the number of analysts in an industry as such variation can help provide insights into the mechanism through which competition affects the quality of analyst reports. In particular, changes in analyst industry competition should be more significant in settings where individual analysts are more important. For example, analyst changes related to competition are likely to have more of an impact for industries with fewer analysts or when the dropped analysts are more knowledgeable. We expect the impact of changes in the number of analysts in an industry to have higher spillover effects when the change is associated with higher quality analysts (e.g., All-Star analysts). Likewise, the change should be more pronounced in industries that have less overall analyst coverage or in industries in which analysts have to devote greater effort to forecast individual firms' earnings.

We also conduct analyses that explicitly consider whether the extent of analyst effort is associated with the level of analyst competition. These tests provide support for one potential mechanism underlying our results—decreased analyst effort. We expect analysts to exert less effort when analyst competition is reduced, resulting in less accurate forecasts as well as more optimistically biased forecasts because the disciplining effect of competition will also be lower.

We further consider the spillover effects of changes in analyst competition by examining how drops in analysts relate to information convergence. Analyst reports are publicly available, and analysts incorporate information from each other in their reports. As analyst competition increases, we expect the degree of information convergence across reports to increase. Analyses that consider more than analyst accuracy and bias help further improve our understanding of sell-side analyst industry competition as a mechanism that affects the quality of analyst reports.

Finally, we also consider the implications of analyst industry competition on market prices. If changes in industry competition produce spillover effects that affect the overall quality of analyst reports in an industry, this should affect price dynamics. We therefore conclude by examining how changes in analyst industry coverage relate to overall stock price movements around analyst reports and earnings announcements at the industry level.

A. Aggregate Forecasting Properties

First, we consider how changes in the number of analysts in the sell-side analyst industry affect aggregate forecasting properties (accuracy and bias). We recognize that naïve regressions of forecasting properties on changes in analyst presence may generate spurious inferences, as omitted variables (e.g., changes in economic conditions) can potentially drive both changes in analyst presence and forecast quality. Accordingly, we construct a measure that captures plausibly exogenous variation in analyst presence based on brokerage house mergers and closures.

Our experiment builds on several recent studies including Kelly and Ljungqvist (2012), Hong and Kacperczyk (2010), and Derrien and Kecskés (2013). Consistent with these studies, we argue that a brokerage house merger/closure creates a plausibly exogenous drop in the number of analysts in an industry and thus provides us with clearer identification of the treatment effect of changes in the total number of analysts. To further enhance the precision of our findings, we drop all firms in an industry that are subject to a direct change in the number of analysts following them. Our results therefore isolate industry spillover effects and do not simply aggregate direct firm-level effects.

We use drops in analysts in an industry from the 52 brokerage house disappearances between 1994 and 2008 examined in Derrien and Kecskés (2013).[15] We employ similar sample procedures and assume that an analyst disappears if there is no earnings estimate for her in I/B/E/S during the year after the broker disappearance date. For broker closures, we retain industries for which an analyst disappears from I/B/E/S and issued a forecast for a firm in that industry in the 12 months prior to the broker closure date. For broker mergers, we retain industries with firms covered by analysts at both the target and the acquirer broker during the 12 months before the merger and for which only one analyst covers following the merger. In Appendix B, we note that dropped firms constitute about 5% of the firms in an industry on average (ranging between 2.6% and 11.0% across industry-months) and 15% of industry market capitalization (ranging between 6% and 31% across industry-months). Perhaps not surprisingly, we find that the percentage of industry market capitalization affected by drops is generally larger than the percentage of industry firms affected. We also find that dropped firms tend to have higher analyst following, since they are statistically more likely to be affected by a brokerage house merger/closure and they are larger than other firms. Prior literature finds that analyst competition affects smaller firms more, suggesting that the nondropped firms we examine could be significantly affected by changes in industry analyst competition. We also note, however, that all of the firms in question have analyst following and nondropped firms are not small firms per se, just smaller on average than dropped firms.

Each month, we compute signed forecast errors for each firm (*FE*) as the difference between the consensus earnings per share (EPS) forecast minus

[15] We thank the authors for sharing these data. For more details on how brokers are identified, please refer to Derrien and Kecskés (2013).

actual EPS, scaled by the absolute value of the consensus EPS forecast, such that more positive forecast errors indicate greater optimism bias. We follow Hribar and McInnis (2012) and exclude firms with absolute consensus forecasts of less than \$0.10 per share from our analysis to avoid issues with small scalars. We average the unsigned (signed) forecast errors for each industry-month after winsorizing the data at the 1st and 99th percentiles to create our measures of aggregate forecast errors. More formally,

$$FE_{i,t} = \frac{1}{n}\sum_{j=1}^{n}\frac{\text{Consensus EPS}_{j,t} - \text{EPS}_{j,t}}{|\text{Consensus EPS}_{j,t}|}, \tag{1}$$

where t denotes month, j denotes firm, and i denotes industry. Note that j includes only those firms that did not experience a change in analyst coverage during the prior month. We compute absolute forecast error as the absolute value of the signed forecast error. Intuitively, aggregate absolute forecast error ($|FE|$) is a proxy for accuracy in industry i in month t and aggregate forecast error (FE) is a proxy for optimism bias in industry i in month t. Similar to prior studies that use aggregate measures of analyst reporting attributes (e.g., Howe, Unlu, and Yan (2009), Hribar and McInnis (2012)), we equal-weight forecast errors because smaller firms are more likely to be affected by changes in analyst activities (Hong and Kacperczyk (2010)). This procedure essentially weights all analyst forecasts equally so as not to obscure the relevant associations (Baker and Wurgler (2006)) and aligns well with our analyst drop measures, which also equally weight individual analyst activity.

To examine the effects of changes in the number of analysts in an industry on earnings forecast accuracy and bias, we estimate

$$\begin{aligned} \textit{Forecast Property}_{i,t} = {} & \alpha_1 \textit{Analyst Drops}_{i,\,t-1} + \gamma \textit{Controls}_{i,t} \\ & + \sum_i \textit{Industry}_i + \sum_m \zeta_m + \varepsilon_{i.t}, \end{aligned} \tag{2}$$

where *Forecast Property* is one of two forecast characteristics: aggregate forecast accuracy ($|FE|$) or aggregate forecast bias (FE) for industry i in period t. The vector of *Controls* includes industry-level *Size*, *Profitability*, *Absolute Change in Profitability*, *Sales Growth*, *Analyst Experience*, and *Market to Book*. Appendix C provides descriptive statistics for the dependent and independent variables employed in the regression analyses. We further include industry fixed effects (*Industry*) to account for time-invariant differences in the quality of aggregate analyst forecasts across industries, as well as a vector of 11 calendar month fixed effects (i.e., February, March, etc.) to account for seasonal differences in analyst forecasting performance as well as horizon effects that vary based on the time remaining until the fiscal period-end.[16] We lag the

[16] The majority of firms in each industry have fiscal periods that end with calendar quarter-ends (i.e., March, June, September, and December). While firm-level analyses in other studies include broker and merger fixed effects, we do not include them in this study, as the structure of our data

change in the number of analysts dropped, *AnalystDrops*, by one month to correct for potential endogeneity with the current period estimates of the forecast properties. Standard errors are clustered by industry and month.

If there are benefits to an increase in the number of analysts in an industry, we expect to see improved accuracy and reduced optimism bias associated with an increase in the number of analysts. When *Forecast Property* $= |FE|$, $\alpha_1 > 0$ implies that a drop in the number of analysts in an industry is associated with reduced accuracy in the next month (i.e., increased aggregate error). When *Forecast Property* $= FE$, $\alpha_1 > 0$ implies that a drop in the number of analysts in an industry is associated with greater optimism bias in the next month. In addition, we expect that if changes in the number of industry analysts are driven by changes in analyst competition, then they should exhibit decreasing returns to scale. In other words, the effect of losing one more additional analyst should flatten off as the number of analysts dropped increases. To test this conjecture, we augment the model to include the square of the number of analysts dropped. A negative coefficient on this term would be consistent with decreasing effects of additional analyst drops.

Panel A of Table II reports the results for forecast accuracy. In columns (1) and (3), we provide the results without controls and in columns (2) and (4) we include industry characteristics. Columns (3) and (4) present the results with the square of the main independent variable included. In columns (1) and (2), the coefficient on *Analyst Drops* suggests that a one-unit drop in the number of analysts in an industry decreases average earnings forecast accuracy by about 1.0% (statistically significant at the 5% level) in absolute terms. Relative to the unconditional mean of the dependent variable, this effect represents a change of about 2.6%. These results suggest that reduced industry analyst competition has negative spillover effects on analyst forecasts for other firms in the industry, consistent with lower analyst effort and information quality. Remaining analysts tend to have higher absolute earnings forecast errors following a drop in the number of industry analysts. Further, columns (3) and (4) of Table II show that this effect is decreasing in the number of analysts dropped, as the squared term is negative and statistically significant. This result is consistent with the view that the effects of a decrease in the number of industry analysts should have decreasing returns to scale.[17]

Panel B of Table II reports the results based on average forecast bias (i.e., signed forecast errors) rather than accuracy (i.e., unsigned forecast errors). In columns (1) and (2), the coefficient on *Analyst Drops* suggests that a one-unit drop in the number of analysts in an industry results in a 1.3% to 1.4% increase in optimistic forecast bias (significant at the 5% level) in absolute terms.

at the industry level is different. In particular, brokerage houses and mergers cover a significant number of industries, making it difficult to isolate these separate effects due to limited variation.

[17] We note that including industry fixed effects and clustering standard errors by industry likely affects the coefficients on many of the control variables. For example, while size is generally expected to be negatively associated with analyst forecast errors at the firm level, it does not load at the industry level. If we remove industry fixed affects and clustering, size is negatively and significantly correlated with industry average forecast errors.

Table II

The Effect of Analyst Following on Forecast Quality

This table provides panel regressions of aggregate industry forecast quality (i.e., accuracy and bias) on drops in aggregate industry-level analyst coverage resulting from brokerage house mergers and closures. Our proxy for accuracy is the industry absolute forecast error ($|FE|$) and our proxy for bias is the industry signed forecast error (FE). We compute these measures as follows. To create a proxy for accuracy (bias), we first compute unsigned (signed) forecast errors for each firm as the absolute value of the difference (the difference) between the monthly EPS and the actual EPS forecast scaled by the absolute value of the consensus EPS forecast. We exclude firm observations that experienced changes in analyst coverage during the preceding month to remove firm-level effects from our analyses. We average the unsigned (signed) forecast errors for each industry-month to create measures of aggregate forecast accuracy (bias). *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. *Analyst Drops*2 is the square of this value. Other control variables include *Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute ΔProfitability* as defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Panel A presents the results for *Accuracy* and Panel B presents the results for *Bias*. Standard errors are clustered by industry and month. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Forecast Accuracy

	(1)	(2)	(3)	(4)
Analyst Drops	0.0105**	0.0105**	0.0203***	0.0207***
	(2.25)	(2.34)	(2.66)	(2.80)
Analyst Drops2			−0.0013***	−0.0013***
			(−2.76)	(−2.89)
Size		0.0093		0.0090
		(0.28)		(0.27)
Profitability		0.0307***		0.0311***
		(4.44)		(4.51)
Sales Growth		−0.0060		−0.0060
		(−1.01)		(−0.99)
Analyst Experience		−0.0006		−0.0006
		(−0.48)		(−0.48)
Market to Book		0.0002		0.0002
		(0.22)		(0.21)
Absolute ΔProfitability		−0.0130		−0.0133
		(−1.30)		(−1.35)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854
R^2	0.32	0.33	0.32	0.33

Panel B: Forecast Bias

	(1)	(2)	(3)	(4)
Analyst Drops	0.0129**	0.0143**	0.0267***	0.0299***
	(2.51)	(2.55)	(3.17)	(3.40)
Analyst Drops2			−0.0018***	−0.0020***
			(−3.46)	(−3.85)
Size		−0.0500		−0.0504
		(−1.63)		(−1.64)

(*Continued*)

Table II—*Continued*

Panel B: Forecast Bias

	(1)	(2)	(3)	(4)
Profitability		0.0307***		0.0313***
		(4.07)		(4.11)
Sales Growth		−0.0049		−0.0048
		(−0.83)		(−0.80)
Analyst Experience		−0.0015		−0.0015
		(−1.41)		(−1.43)
Market to Book		0.0008		0.0008
		(1.09)		(1.07)
Absolute ΔProfitability		−0.0105		−0.0110
		(−0.78)		(−0.82)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854
R^2	0.19	0.21	0.19	0.22

Relative to the unconditional mean of the dependent variable, this effect represents a change of about 5.5%. Consistent with the accuracy results, the squared term in columns (3) and (4) is also negative and significant (i.e., decreasing returns to scale). These results suggest that the spillover effects of changes in analyst competition also relate to analysts' incentives to be optimistically biased, suggesting that industry competition disciplines analyst reports. In analyses reported in the Internet Appendix, we also consider the effects of drops of analyst coverage on recommendation bias. Consistent with the earnings forecasts results, we find that drops in analyst coverage are associated with more optimistic recommendations, higher likelihood of buy recommendations, and lower likelihood of sell recommendations. We also find that the effect of analyst drops on earnings forecast bias is more economically significant when we measure drops based on the number of skeptical analysts that are no longer covering the industry, where skeptical analysts are defined as analysts that have at least one outstanding sell recommendation (tabulated in the Internet Appendix).

Overall, these results provide a consistent message that decreases in analyst competition at the industry level adversely affect the overall quality of analyst reports—not only for the firms that lose an analyst, but also for other firms in the same industry. We find that decreases in the total number of analysts negatively affect two important dimensions of analyst reports: forecast accuracy and bias.[18] The results, which exclude firm-level direct effects, show that changes

[18] Given that brokerage house mergers and closures only relate to analyst drops, we cannot address whether increases in industry analysts would have a similar effect. We can, however, consider this difference using overall changes in industry analysts, which we do in Section III.A. We find that overall changes in industry analysts are also negatively associated with analyst forecast accuracy and bias, but we are unable to find any statistical difference between increases and decreases in analysts. It is important to note, however, that these tests are limited by potential endogeneity problems.

in the number of analysts at the industry level have spillover effects that extend beyond those documented in firm-level studies. That is, industry analyst competition is a distinct form of competition that affects the quality of information analysts provide to market participants. To further address differences in the effect of firm-level versus industry-level mechanisms, in Section III.B, we perform additional tests that shed more light on the relative importance of these two aspects of competition.

B. Cross-Sectional Variation in the Impact of the Change in the Number of Analysts

If, as our findings suggest, industry competition is a significant factor affecting analyst report quality, then industries that are subject to varying competitive pressures should experience different effects when analysts drop from their industry. Likewise, the impact of analyst drops should also vary with the quality of analysts leaving the industry. For instance, analysts who possess higher quality information or better skill should have a greater effect on the level of competition and consequently on changes in both forecast accuracy and bias. In this subsection, we explore these types of questions to better identify the mechanism through which industry analyst drops affect the quality of information that analysts provide to market participants for firms not directly related to these changes.

First, we examine how our results vary with the number of analysts covering an industry. Similar to Hong and Kacperczyk (2010), we argue that the information produced by analysts and the competition between them is related to the number of analysts in an industry. Specifically, we expect the effect of analyst drops to be lower for industries that have a large number of analysts because the role of individual analysts in these industries is less significant. We classify an industry-year as having high analyst coverage (*High Coverage*) if it is above the sample median number of analysts. We then interact this indicator with the number of drops.

Table III reports the results. The coefficient on the interaction between the number of analyst drops and high coverage is negative and significant ($p < 0.05$) when we consider average industry absolute forecast error in columns (1) and (2). This suggests that drops in analyst coverage have a less significant effect on average forecast accuracy for industries with higher analyst coverage. When we consider the effect on forecast bias in columns (3) and (4), the coefficient on the interaction term is also negative and significant ($p < 0.10$). Thus, the industry spillover effect of drops in analysts on the quality of reports is larger in industries with fewer analysts. We also find similar results when we partition industry-months into quintiles of analyst coverage in that we observe that the effects of drops in analysts on accuracy and bias are generally monotonically decreasing in the extent of industry analyst coverage.

Second, we examine whether our results depend on the ease with which analysts forecast earnings for individual firms in an industry. When firms'

Table III

Industry Information Environment, Analyst Following, and Forecast Quality

This table provides panel regressions of aggregate industry forecast quality (i.e., accuracy and bias) on drops in aggregate industry-level analyst coverage resulting from brokerage house mergers and closures interacted with *High Analyst Following*. *Accuracy* and *Bias* are as defined in Table II. *High Following* is an indicator variable that takes the value of one if industry-level analyst following is above the sample median, and zero otherwise. *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. Other control variables include *Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute ΔProfitability* as defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Standard errors are clustered by industry and month. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	DV = Accuracy		DV = Bias	
	(1)	(2)	(3)	(4)
Analyst Drops	0.0274***	0.0274***	0.0272**	0.0301***
	(2.94)	(3.01)	(2.47)	(2.60)
Analyst Drops × High Following	−0.0206**	−0.0209***	−0.0173*	−0.0196*
	(−2.56)	(−2.68)	(−1.73)	(−1.93)
High Following	−0.0796*	−0.0818*	−0.0648	−0.0485
	(−1.80)	(−1.76)	(−1.49)	(−0.96)
Size		0.0160		−0.0461
		(0.47)		(−1.47)
Profitability		0.0286***		0.0296***
		(4.61)		(3.99)
Sales Growth		−0.0054		−0.0045
		(−0.96)		(−0.81)
Analyst Experience		−0.0008		−0.0016
		(−0.66)		(−1.58)
Market to Book		0.0004		0.0010
		(0.60)		(1.34)
Absolute ΔProfitability		−0.0141		−0.0113
		(−1.38)		(−0.83)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854
R^2	0.33	0.34	0.19	0.22

earnings are easy to forecast, drops in industry analysts likely have less of an impact because there is less value in having more analysts. To test this conjecture, we measure the ease with which analysts forecast the earnings of individual firms in an industry based on the extent to which earnings are correlated across an industry, (i.e., industry earnings synchronicity). We expect that analysts can more easily forecast the earnings of firms in an industry that has highly correlated earnings and depends less on idiosyncratic differences across firms. In addition, we expect drops in analysts to have a less significant effect when individual firms matter less because less information is lost when individual analysts drop from the industry and no longer provide reports on some firms.

Similar to Morck, Yeung, and Yu's (2000) analysis at the country level, we calculate earnings synchronicity at the industry level by first estimating firm-level regressions of industry return on assets (*ROA*) on firm-level ROA using quarterly earnings data over rolling five-year windows. Specifically, we estimate

$$ROA_{j,i,t} = \alpha_j + \beta_j ROA_{i,t} + \varepsilon_{j,t}, \tag{3}$$

where t denotes quarter, j denotes firm, and i denotes industry. We include only those firms with analyst coverage on I/B/E/S and construct the industry ROA based on the market-cap-weighted average of each firm. We then construct industry earnings synchronicity as the value-weighted R^2 from these regressions. We classify an industry-year as having high earnings synchronicity (*High Earnings Synch*) if the industry-year R^2 is above the sample median. We then interact this indicator with the number of drops.

Table IV reports the results. Columns (1) and (2) report the results for analyst forecast accuracy. The coefficient on the interaction between the number of analyst drops and the high coverage indicator is negative and significant ($p <$ 0.01), suggesting that drops in analysts have a less significant effect on average forecast accuracy for industries with higher earnings synchronicity. In fact, the coefficients indicate that the effect of drops in industry analysts is about 78% (–0.0133/0.0170) smaller for these industries. This result is consistent with individual analysts mattering less for industries in which analysts can more easily forecast individual firms' earnings (i.e., industries in which individual firms matter less). Columns (3) and (4) report the results for forecast bias. The coefficient on the interaction term in this regression is also negative and significant ($p < 0.05$), suggesting that the effect of analyst drops on forecast bias also relates to industry earnings synchronicity. The difference for bias is high as well. The coefficients indicate that the effect of industry analyst drops is about 52% (–0.0088/0.0170) lower for industries with high earnings synchronicity. These results suggest that information spillovers are potentially one mechanism through which analyst competition affects the quality of analyst reports, as we find that the effects of competition are lower when analyst information is less important.

Finally, we examine the effect of drops that involve II All-Star analysts. All-Star analysts are generally viewed as higher quality analysts. These analysts provide reports of superior information quality and their reports often receive more attention than those of other analysts (Loh and Stulz (2011)). In addition, All-Star analysts are often viewed as personal rivals by other analysts (Reingold (2006)). These factors can intensify the competition between All-Star analysts and other analysts, which suggests that losing an All-Star analyst should have a more significant effect on the information production of other analysts as well as on the intensity of competition between analysts. This prediction is not without tension, however, as it is also possible that the loss of

Table IV

Industry Earnings Synchronicity, Analyst Following, and Forecast Quality

This table provides panel regressions of aggregate industry forecast quality (i.e., accuracy and bias) on drops in aggregate industry-level analyst following resulting from brokerage house mergers and closures interacted with industry R^2. *Accuracy* and *Bias* are as defined in Table II. *High* R^2 is an indicator variable set to one for industries with above-median value-weighted R^2s, based on a firm-specific regression of industry earnings on firm earnings following Morck, Yeung, and Yu (2000). *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. Other control variables include *Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute* Δ*Profitability* as defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Standard errors are clustered by industry and month. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	DV = Accuracy		DV = Bias	
	(1)	(2)	(3)	(4)
Analyst Drops	0.0170***	0.0167***	0.0170***	0.0185***
	(3.33)	(3.33)	(3.62)	(3.33)
Analyst Drops × High R^2	−0.0133***	−0.0129***	−0.0088**	−0.0088**
	(−3.79)	(−3.57)	(−2.54)	(−2.13)
High R^2	0.0000	0.0002	−0.0183	−0.0169
	(0.00)	(0.01)	(−0.75)	(−0.71)
Size		0.0091		−0.0504
		(0.27)		(−1.64)
Profitability		0.0302***		0.0308***
		(4.55)		(4.24)
Sales Growth		−0.0060		−0.0048
		(−1.01)		(−0.80)
Analyst Experience		−0.0006		−0.0014
		(−0.46)		(−1.31)
Market to Book		0.0002		0.0008
		(0.23)		(1.07)
Absolute ΔProfitability		−0.0133		−0.0108
		(−1.35)		(−0.80)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854
R^2	0.32	0.33	0.19	0.22

an All-Star analyst could lead to an increase in competition as analysts vie for the open spot.

We empirically test this question by including an indicator variable for drops involving All-Star analysts (*All-Star Drop*) and interacting this indicator with the number of analysts dropped. Table V reports the results. The coefficient on the interaction between the number of analyst drops and the All-Star analyst indicator is positive and significant ($p < 0.05$) in columns (1) and (2), suggesting that the effect of analyst drops on absolute forecast error is stronger when such drops involve All-Star analysts. When we consider the effects of analyst drops

Table V

Knowledgeable Analysts, Analyst Following, and Forecast Quality

This table provides panel regressions of aggregate industry forecast quality (i.e., accuracy and bias) on drops in aggregate industry-level analyst coverage resulting from brokerage house mergers and closures interacted with All-Star analyst drops. *Accuracy* and *Bias* are as defined in Table II. *All Star Drop* is an indicator variable that takes the value of one if an industry has lost an All-Star analyst in the past three years, and zero otherwise. *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. Other control variables include *Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute* Δ*Profitability* as defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Standard errors are clustered by industry and month. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	DV = Accuracy		DV = Bias	
	(1)	(2)	(3)	(4)
Analyst Drops	0.0087**	0.0086**	0.0113**	0.0123**
	(2.09)	(2.06)	(2.35)	(2.31)
Analyst Drops × All Star Drop	0.0121**	0.0129**	0.0073	0.0087
	(2.17)	(2.52)	(1.37)	(1.49)
All Star Drop	−0.0012	−0.0059	0.0227	0.0259
	(−0.02)	(−0.12)	(0.50)	(0.53)
Size		0.0092		−0.0501
		(0.28)		(−1.64)
Profitability		0.0304***		0.0304***
		(4.47)		(3.95)
Sales Growth		−0.0061		−0.0049
		(−1.02)		(−0.82)
Analyst Experience		−0.0006		−0.0015
		(−0.49)		(−1.42)
Market to Book		0.0002		0.0008
		(0.26)		(1.16)
Absolute ΔProfitability		−0.0134		−0.0108
		(−1.32)		(−0.80)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854
R^2	0.32	0.33	0.19	0.21

on optimism bias, we find that the coefficient on the interaction between the number of analyst drops and All-Star analysts is positive but not significant at conventional levels. In general, these results suggest that All-Star analyst drops have a more significant effect on the activities of their peers, consistent with industry competition being driven at least in part by the most talented analysts in an industry.

Overall, the cross-sectional analyses support the notion that industry-level competition appears to be an important factor affecting analyst behavior. The effects of analyst drops are more pronounced when industries have fewer analysts, less pronounced when firms' earnings are easy to forecast, and more pronounced when drops involve an All-Star analyst. These findings highlight the uniqueness of industry-level analyst following and suggest that industry-level competition is an important force in the sell-side equity analyst industry.

C. Analyst Effort

As previously explained, one of the mechanisms through which competition affects the quality of analyst reports is its effect on analyst effort. Analysts should exert less effort when competition decreases. While our previous tests relate to this issue, they do not specifically isolate analyst effort. To better examine the effect of analyst competition on effort, we consider several measures of effort that we divide into four groups: (1) analyst participation, (2) report timing, (3) breadth of report coverage, and (4) conference call behavior.

First, we measure effort based on analyst participation in terms of providing reports to market participants. We expect drops in analysts to negatively affect the extent to which analysts provide information to capital markets. We capture a proxy for participation using several measures. We define *%Analyst Participation* as the percentage of analysts in an industry who were considered active analysts in period $t-2$ and provide at least one report in period t after a drop in industry analysts occurs in period $t-1$. (Note: an active analyst is defined as any analyst providing a forecast in the 12-month period ending in $t-2$, where drops occur in period $t-1$.) If any analyst is dropped in period $t-1$, the analyst in not considered in either the numerator or the denominator of this ratio. Similarly, we define *%Recommendations* as the percentage of analysts in an industry who were considered active analysts in period $t-2$ and provide at least one recommendation in period t. In addition, we define *Forecasts per Analyst* as the number of reports issued by industry analysts who provide at least one report in period t divided by the number of analysts who were considered active analysts in period $t-2$.

Second, we measure analyst effort in terms of how soon analysts provide reports after the beginning of period t, where drops occur in period $t-1$. Prior studies suggest that analyst effort and ability relate to the timeliness of their reports (e.g., Hong, Lim, and Stein (2000), Cooper, Day, and Lewis (2001)). We expect drops in analysts to be positively related to report timing, as analysts should take longer to issue reports when they exert less effort. We define *Report Timing* as the number of days between the end of period $t-1$ and the first report made by analysts in the subsequent three months.

Third, we measure analyst effort in terms of the breadth of analysts' reporting coverage. We expect analyst drops to negatively affect the breadth of analysts' coverage for firms that already receive coverage as well as for new firms. We define *%Previous_Firms* as the number of nondropped firms that were actively covered in $t-2$ and received at least one report in t divided by the number of nondropped firms that were actively covered in $t-2$. Similarly, we define *%New_Firms* as the number of new firms that were not actively covered in $t-2$ and received at least one report in t divided by the number of nondropped firms that were actively covered in $t-2$.

Finally, we measure effort based on analyst conference call behavior. Prior studies find that conference calls provide an important information channel for analysts, but that the informativeness of this channel can be limited by conflicts of interest between analysts and managers (e.g., Bowen, Davis, and Matsumoto (2002), Mayew (2008), Matsumoto, Pronk, and Roelofsen (2011), Cohen, Lou, and Malloy (2012), Allee and DeAngelis (2015)). We examine analyst conference call behavior based on the difficulty of the questions analysts ask and expect analyst drops to result in analysts asking less difficult questions. Recent studies show that text length is associated with complexity (e.g., Lehavy, Li, and Merkley (2011), Loughran and McDonald (2014)), which suggests that more difficult analyst questions should be longer. In addition, Cohen, Lou, and Malloy (2012) find that analysts with higher recommendations ask shorter questions, consistent with analyst conflicts of interest being related to question length. We measure analyst question length using a sample of conference calls obtained from SeekingAlpha.com between 2004 and 2010 and isolate analyst speech following Allee and DeAngelis (2015). We define *Question_Length* as the average length of the questions asked by analysts in conference calls that took place during the three months following a drop (i.e., t, $t + 1$, and $t + 2$). We calculate this measure as the ratio of the number of words spoken by analysts in the call to the number of questions asked.

Table VI reports the results of regressing measures of analyst effort on drops in analysts. Across all measures, the results provide evidence consistent with analyst drops negatively affecting analyst effort. Specifically, the results suggest that drops are negatively related to analyst participation (columns (1) to (3)), positively related to report timing (column (4)), negatively related to the breadth of reporting coverage (columns (5) and (6)), and negatively related to conference call question difficulty (column (7)). These findings are consistent with changes in analyst competition affecting the quality of analyst reporting through changes in analyst effort and help establish a potential mechanism underlying our results.

D. Analyst Information Convergence

To provide further evidence regarding the effects of analyst competition, we consider whether analyst drops in an industry affect the degree of information convergence. Since analyst reports are publicly available and analysts incorporate information provided in peer reports, analyst reports in an industry are likely to converge as the degree of common information increases. Moreover, as competition increases, analysts are likely to pay more attention to the reports of their peers, leading to higher convergence of reporting outputs. As such, we expect that analyst reports should have lower information convergence when an industry experiences drops in analysts

We measure the degree of analyst information convergence based on aggregate analyst earnings forecast dispersion. Following prior studies, we calculate dispersion at the firm level as the standard deviation of analyst forecasts scaled by stock price. We then aggregate this measure at the industry-month level as

Table VI

The Effect of Analyst Following on Analyst Effort

This table provides panel regressions of measures of aggregate industry analyst effort on drops in aggregate industry-level analyst coverage resulting from brokerage house mergers. The effort measures are described in Appendix A. *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. The effort measures and the control variables (*Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute* Δ*Profitability*) are defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Standard errors are clustered by industry and month. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	%Analyst Participation	%Recommendations	Forecasts per Analyst	Report Timing	%Previous Firms	%New Firms	Question Length
Analyst Drops	−0.0110***	−0.0026***	−0.0539***	0.3707***	−0.0146***	−0.0010***	−0.3454***
	(−4.90)	(−3.14)	(−3.71)	(3.78)	(−5.08)	(−3.41)	(−2.82)
Size	0.0492***	0.0207**	0.3275***	1.1302*	0.0182	−0.0076***	1.8717
	(4.75)	(2.34)	(3.58)	(1.81)	(1.01)	(−5.33)	(0.46)
Profitability	0.0056*	−0.0050***	−0.0001	−0.4099**	0.0125	0.0014	1.2281***
	(1.86)	(−3.05)	(−0.00)	(−2.18)	(1.59)	(1.43)	(3.71)
Sales Growth	0.0039*	−0.0007	0.0103	0.1290	0.0011	−0.0000	0.4028**
	(1.93)	(−0.59)	(0.61)	(0.82)	(0.28)	(−0.06)	(1.96)
Analyst Experience	0.0009*	−0.0010***	0.0097	−0.0815***	−0.0006	−0.0001	0.2073***
	(1.88)	(−3.49)	(1.61)	(−3.30)	(−0.78)	(−1.13)	(2.64)
Market to Book	0.0000	−0.0001	−0.0009	0.0014	0.0002	0.0000	−0.0503*
	(0.02)	(−1.00)	(−0.42)	(0.13)	(0.48)	(0.12)	(−1.77)
Absolute ΔProfitability	−0.0000	−0.0001***	−0.0006***	0.0004	0.0001**	0.0000***	0.0049***
	(−0.16)	(−2.97)	(−2.76)	(0.43)	(2.34)	(5.15)	(4.25)
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,854	4,834	5,854	5,854	5,854	5,854	1,093
R^2	0.535	0.516	0.668	0.434	0.434	0.109	0.418

previously described for the other dependent variables. Table VII reports the results. Consistent with our expectations, we find that drops in industry analysts are associated with higher aggregate forecast dispersion, consistent with lower information convergence. This evidence, together with our finding regarding analyst effort, sheds further light on the mechanism underlying our accuracy and bias results, as we find that the flow of common information among analysts in an industry is also related to analyst drops.

E. Market Consequences

Our previous results suggest that the quality of the information that analysts convey to the market is lower when fewer analysts cover an industry. Lower quality analysts' reports due to decreased competition at the industry analyst level should also have consequences for valuation: lower quality

Table VII

The Effect of Analyst Following on Analyst Information Convergence

This table provides panel regressions of measures of aggregate analyst information convergence on drops in aggregate industry-level analyst coverage resulting from brokerage house mergers. Analyst information convergence is calculated as the industry average dispersion in analyst earnings forecasts. *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. The effort measures and the control variables (*Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute* Δ*Profitability*) are defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Standard errors are clustered by industry and month. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Analyst Drops	0.0017**	0.0015**
	(2.13)	(2.17)
Size		0.0020
		(1.14)
Profitability		−0.0016
		(−0.82)
Sales Growth		−0.0014***
		(−2.85)
Analyst Experience		−0.0001
		(−0.96)
Market to Book		−0.0001
		(−0.89)
Absolute ΔProfitability		−0.0010
		(−0.70)
Month FE?	Yes	Yes
Industry FE?	Yes	Yes
Observations	5,854	5,854
R^2	0.40	0.41

reports lead to reports that have less information content and thus should have less of an impact on market prices. In other words, if drops in analyst coverage result in lower information production in an industry and in turn lower quality reports, then analyst reports in affected industries should provide less new information to capital markets. In contrast, other corporate events that contain information about earnings should have a more pronounced impact on prices. In particular, as analyst reports and earnings announcements can sometimes be thought of as substitutes that convey information to the market (Chen, Cheng, and Lo (2010)), when the information content in analyst reports is lower, the information content in subsequent earnings announcements should be higher.

Similar to the firm-level analyses of Frankel, Kothari, and Weber (2006) and Lehavy, Li, and Merkley (2011), we compute a monthly measure of aggregate analyst informativeness (*AI*). For each firm, we compute *AI* by summing the absolute size-adjusted returns for all forecast revision dates in a given month and then divide this amount by the sum of all absolute size-adjusted returns for all trading days in a month. Then, for each industry-month, we average all firm analyst informativeness ratios across all firms in an industry that did not experience a change in analyst following. Formally,

$$Analyst\ INFO_{i,t} = \frac{1}{n} \sum_{j=1}^{n} AI_{j,t} \tag{4}$$

$$AI_{i,t} = \frac{\sum_{d=1}^{NREVS} \left|Ret_{j,d} - Dec\ Ret_{j,d}\right|}{\sum_{d=1}^{20} \left|Ret_{j,d} - Dec\ Ret_{j,d}\right|}, \tag{5}$$

where d denotes trading days in a month, *NREVS* denotes the number of unique days for which there is at least one analyst forecast, j denotes firm, i denotes industry, and t denotes month. We measure returns (*Ret*) as the daily return obtained from the CRSP Daily Stock File. Further, *DecRet* is the size decile adjusted return obtained from the CRSP Portfolio file.

While *AI* captures analyst informativeness, we also construct an aggregate measure of earnings announcement information content (*EAINFO*) based on stock return information around earnings dates, similar to prior studies such as Francis, Schipper, and Vincent (2002). We first collect all quarterly earnings announcement dates from I/B/E/S that fall within five days of the firm's quarterly report date (obtained from Compustat) to reduce the possibility that the dates represent a data error on I/B/E/S (DellaVigna and Pollet (2009)). We then calculate size-adjusted absolute cumulative abnormal returns (*ACAR*) for each firm for the three-day window around the earnings announcement. Next, for each industry-month, we average all of the *ACAR*s for firms within the industry that did not experience a change in analyst following. Formally:

$$EAINFO_{i,t} = \frac{1}{n} \sum_{j=1}^{n} ACAR_{j,t} \tag{6}$$

$$ACAR_{i,t} = \sum_{d=-1}^{1} \left|Ret_{j,d} - Dec\ Ret_{j,d}\right|, \tag{7}$$

where d denotes days around a firm's earnings announcement date, j denotes firm, i denotes industry, t denotes month, and *Ret* and *DecRet* are as defined previously.

There are potential concerns with both the *AI* and *EAINFO* measures. One potential concern for the *AI* measure is that analysts could "piggyback" on management disclosures. If *AI* includes analyst reports that immediately follow management disclosures, analyst reports could appear to provide more information than they actually do. Using intraday returns, Altinkilic and Hansen (2009) and Altinkilic, Balashov, and Hansen (2013) argue that analysts' reports provide little new information on average because they frequently follow significant news releases. However, Bradley et al. (2014) show that these results are driven by systematically delayed time stamps. After adjusting for this bias, analyst reports are still one of the most important information channels. To provide some comfort that our analyses are unlikely to be driven by "piggybacking," we exclude from our analyst informativeness measure those analyst report days within a three-day window around earnings announcements and those corresponding to management earnings forecast dates available in the First Call CIG database, as these disclosures represent some of the most significant earnings information events.

A potential concern with the *EAINFO* measure is that earnings announcements could be less informative when there are more analysts covering a firm. This is because these managers might release earnings news earlier via management earnings forecasts to meet analysts' information demands. However, it is also possible that such earnings announcements would be more informative because these earnings announcements are also more likely to be accompanied by management forecasts as most management forecasts are disclosed in earnings announcements (Rogers and Van Buskirk (2013)). These issues are unlikely to be a concern in our setting because we examine firms that experience changes in analysts in their industry, but not changes that directly affect the number of analysts covering these firms. Managers are unlikely to have strong information demands related to analysts who do not directly cover their firm.

Using these measures, we examine how drops in the number of industry analysts relate to the price informativeness of analyst reports and earnings announcements, using the following model:

$$\begin{aligned} \mathit{Info\ Type}_{i,t} &= \alpha_1 \mathit{Analyst\ Drops}_{i,\ t-1} + \gamma \mathit{Controls}_{i,t} \\ &\quad + \sum_i \mathit{Industry}_i + \sum_m \zeta_m + \varepsilon_{i.t}, \end{aligned} \tag{8}$$

where *InfoType* is one of two informativeness measures: *AnalystINFO* or *EAINFO*. The vector of controls contains the same set of control variables as in equation (2) above (i.e., *Size*, *Profitability*, *Absolute Change in Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*). As in other tests, we conduct these analyses based on firms that experience an indirect drop in analyst coverage because other firms in the industry lose analyst coverage. Our measures exclude firm observations that experience direct changes in analyst coverage. We expect that analyst drops should decrease the informativeness of analyst reports while potentially increasing the informativeness of earnings announcements. If this is the case, we expect $\alpha_1 < 0$ when we examine the price impact of analysts' reports (*AnalystINFO*) and $\alpha_1 > 0$ when we examine the price impact of earnings reports (*EAINFO*).

Table VIII reports the results from these tests. In Panel A, we examine the effect of changes in the number of analysts on the informativeness of analyst reports. Columns (1) and (3) provide the results excluding industry characteristics and columns (2) and (4) include these controls. Similar to our analyses examining forecast quality, we also include squared terms in columns (3) and (4). Consistent with our expectations, decreases in analysts related to brokerage house mergers and closures reduce the average informativeness of analyst

Table VIII

The Effect of Analyst Following on Public Disclosure Informativeness

This table provides panel regressions of aggregate industry informativeness measures on drops in aggregate industry-level analyst coverage resulting from brokerage house mergers and closures. Our aggregate industry informativeness measures include the informativeness of analyst reports (*AnalystINFO*) and the informativeness of earnings announcements (*EAINFO*). *AnalystINFO* is calculated by averaging firm-level analyst informativeness (*AI*) across all firms within an industry-month, where *AI* is the absolute size-adjusted returns on forecast revision dates in a given month divided by the sum of all absolute size-adjusted returns for all trading days in a month. *EAINFO* is calculated by averaging all firm absolute cumulative abnormal returns (*ACAR*) within a three-day window around the earnings announcement within an industry-month. For both measures, we exclude firm observations that experienced changes in analyst coverage during the preceding month to remove firm-level direct effects from our analyses. *Analyst Drops* is the number of analyst drops resulting from brokerage house mergers and closures. *Analyst Drops2* is the square of this value. Other control variables are defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Panel A presents the results for *AnalystINFO* and Panel B presents the results for *EAINFO*. Standard errors are clustered by industry and month. *t*-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AnalystINFO

	(1)	(2)	(3)	(4)
Analyst Drops	−0.0024***	−0.0021***	−0.0042***	−0.0039***
	(−3.52)	(−3.10)	(−3.45)	(−3.16)
Analyst Drops2			0.0002**	0.0002**
			(2.57)	(2.44)
Size		−0.0036		−0.0036
		(−1.06)		(−1.05)
Profitability		0.0018		0.0017
		(1.29)		(1.24)
Sales Growth		−0.0003		−0.0003
		(−0.27)		(−0.29)
Analyst Experience		0.0004*		0.0004*
		(1.65)		(1.66)
Market to Book		−0.0001		−0.0001
		(−0.90)		(−0.87)
Absolute ΔProfitability		0.0041*		0.0042*
		(1.92)		(1.94)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854
R^2	0.32	0.33	0.32	0.33

Panel B: EAINFO

	(1)	(2)	(3)	(4)
Analyst Drops	0.0032***	0.0028***	0.0047***	0.0042***
	(3.37)	(3.03)	(3.02)	(2.82)
Analyst Drops Sqr.			−0.0002	−0.0002
			(−1.50)	(−1.37)
Size		0.0113***		0.0112***
		(2.96)		(2.95)

(*Continued*)

Table VIII—*Continued*

Panel B: EAINFO

	(1)	(2)	(3)	(4)
Profitability		0.0012		0.0013
		(0.41)		(0.43)
Sales Growth		−0.0014		−0.0014
		(−1.31)		(−1.29)
Analyst Experience		−0.0002		−0.0002
		(−1.05)		(−1.06)
Market to Book		−0.0000		−0.0000
		(−0.53)		(−0.55)
Absolute ΔProfitability		−0.0043		−0.0043
		(−1.52)		(−1.53)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,661	5,661	5,661	5,661
R^2	0.25	0.27	0.26	0.27

reports of other stocks in the same industry by about 0.2% ($p < 0.01$, columns (1) and (2)). Relative to the unconditional mean of the dependent variable, this effect represents a change of about 2.0%. In columns (3) and (4), we further find that this effect exhibits decreasing returns to scale as the squared number of analysts involved in a drop increases, similar to our results in Table II for forecast accuracy and bias. The coefficient on squared analyst drops is positive and significant ($p < 0.05$).

In Panel B, we examine the effect of changes in analysts on the average informativeness of earnings announcements. We find that a one-unit drop in the number of analysts related to brokerage house mergers and closures increases the average price impact of earnings announcements by about 0.3% ($p < 0.01$, columns (1) and (2)). Relative to the unconditional mean of the dependent variable, this effect represents a change of about 3.3%. In columns (3) and (4), we continue to find only weak evidence that the earnings announcement effect also exhibits decreasing returns to scale (not significant at conventional significance levels). The results of our analysis remain unchanged when we exclude dates with multiple analyst reports as in Loh and Stulz (2011).

Taken together, the results in Table VIII suggest that decreasing the number of analysts providing coverage within an industry can decrease the overall flow of information, thereby limiting the dissemination of important value-relevant information to investors before the earnings announcement date. These findings are consistent with firm-level evidence suggesting that analysts serve an "information discovery" role in the period leading up to the earnings announcement (Chen, Cheng, and Lo (2010)), and suggest that this process is also a function of the extent of overall analyst presence in an industry. However, to the extent that the information analysts provide is industry-specific rather than firm specific, our industry-level tests are better able to capture improvements in information flow than prior firm-level studies.

III. Additional Analyses

A. External Validity

Examining drops in analysts resulting from brokerage house mergers and closures provides us with a plausibly exogenous setting to identify the effects of industry changes in analyst coverage. However, one limitation of this analysis is that it restricts our focus to only industry drops and limits the external validity of our tests. For example, our tests are unable to speak directly to the effects of increases in analyst coverage or changes in analyst coverage during periods of time in which there were no brokerage house mergers or closures. In this section, we complement our main analysis by examining the effects of *all changes* in analyst industry coverage.

While potentially more endogenous, using overall changes in analyst industry coverage allows us to examine the external validity of our findings beyond the setting that our natural experiment allows. To consider overall changes in analyst industry coverage, we examine three measures of changes in analyst industry coverage: (1) the number of drops based on brokerage mergers and closures as in the prior analyses ($\Delta Analyst^{Drops}$), (2) the overall net change in analysts in an industry ($\Delta Analyst^{All}$), and (3) the difference between the net change and the number of drops ($\Delta Analyst^{Other}$). Table IX reports the results of this analysis. Using the sample containing all changes in the number of analysts covering an industry suggests that, in general, a reduction in the number of analysts in an industry is associated with decreased forecast accuracy and increased forecast optimism.[19] Interestingly, these effects are an order of magnitude larger for exogenous changes in analyst coverage (i.e., $\Delta Analyst^{Drops}$), consistent with the finding in Hong and Kacperczyk (2010) that better identification allows for a clearer and larger identification of the treatment effect.

B. Firm-Level versus Industry-Level Competition

Using the same exogenous drop in the number of analysts, Hong and Kacperczyk (2010) document a significant competitive effect at the firm level. Specifically, they find that when a firm loses an analyst, it experiences an increase in the consensus forecast bias. That is, the reduction in firm-level analyst competition negatively affects the quality of the forecasts of the other analysts following the firm. It is important to compare the effects of changes in analyst competition at the firm level (Hong and Kacperczyk (2010)) with those of changes in industry-level competition. Throughout the analyses, we clearly distinguish changes in industry-level competition from changes in firm-level

[19] We are unable to find evidence of a statistical difference between increases and decreases in analysts if we partition $\Delta Analyst^{All}$ into separate variables for increases and decreases.

Table IX

General Changes in Analysts Following and Industry Forecast Quality

This table provides panel regressions of aggregate industry forecast quality (i.e., accuracy and bias) on changes in industry analyst following. Our proxy for accuracy is the industry absolute forecast error ($|FE|$) and our proxy for bias is the industry signed forecast error (FE), as defined in Table II. $\Delta Analysts^{Drops}$ is the number of analyst drops resulting from brokerage house mergers and closures. $\Delta Analysts^{All}$ is the total monthly change in analysts. $\Delta Analysts^{Other}$ is the difference between $\Delta Analysts^{All}$ and $\Delta Analysts^{Drops}$. Other control variables include *Size*, *Profitability*, *Sales Growth*, *Analyst Experience*, *Market to Book*, and *Absolute* Δ*Profitability* as defined in Appendix A. All regression results are based on monthly measures of variables across 24 GICS industry groups from 1990 to 2010. Standard errors are clustered by industry and month. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	DV = Accuracy			DV = Bias		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔAnalyst^{Drops}	−0.0105**		−0.0109**	−0.0143**		−0.0148***
	(−2.34)		(−2.41)	(−2.55)		(−2.59)
ΔAnalyst^{All}		−0.0024***			−0.0030***	
		(−2.79)			(−2.74)	
ΔAnalyst^{Other}			−0.0020**			−0.0025**
			(−2.36)			(−2.29)
Size	0.0093	0.0114	0.0098	−0.0500	−0.0472	−0.0494
	(0.28)	(0.34)	(0.29)	(−1.63)	(−1.55)	(−1.62)
Profitability	0.0307***	0.0304***	0.0310***	0.0307***	0.0304***	0.0312***
	(4.44)	(4.36)	(4.51)	(4.07)	(3.95)	(4.07)
Sales Growth	−0.0060	−0.0054	−0.0054	−0.0049	−0.0040	−0.0042
	(−1.01)	(−0.89)	(−0.90)	(−0.83)	(−0.68)	(−0.69)
Analyst Experience	−0.0006	−0.0007	−0.0006	−0.0015	−0.0017	−0.0016
	(−0.48)	(−0.59)	(−0.52)	(−1.41)	(−1.57)	(−1.48)
Market to Book	0.0002	0.0002	0.0002	0.0008	0.0009	0.0008
	(0.22)	(0.30)	(0.25)	(1.09)	(1.23)	(1.15)
Absolute ΔProfitability	−0.0130	−0.0160	−0.0150	−0.0105	−0.0143	−0.0129
	(−1.30)	(−1.61)	(−1.54)	(−0.78)	(−1.04)	(−0.96)
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,854	5,854	5,854	5,854	5,854	5,854
R^2	0.33	0.33	0.33	0.21	0.21	0.22

competition. We exclude all firms that experience a change in the number of analysts to isolate only the effect on all other firms in the industry. We perform all previous tests at the industry level because we are primarily interested in understanding how changes in industry analyst competition affect the overall industry in which analysts work. Thus, by construction, the previous analyses are unable to compare differences in the economic magnitudes of changes in analyst competition at the firm and industry levels.

To facilitate direct comparisons with the results of Hong and Kacperczyk (2010), we must perform additional analyses at the firm level. It is important to note that while this level can provide insights about the relative impact of firm-level and industry-level analyst drops, it does not necessarily capture the aggregate industry effects examined in our previous analyses. Firm-level analyses are informative about how drops in analysts from a firm's industry affect a single firm's analyst reports, rather than about the aggregate effect for all firms in an industry. In firm-level analyses each firm receives equal weight in identifying the effects of drops, while in industry analyses firms are weighted differently because they are aggregated at the industry level first.

To perform the firm-level analyses, we follow Hong and Kacperczyk (2010) and use both an ordinary least squares (OLS) approach based on the level of analyst coverage and a difference-in-differences (DID) matching approach based on exogenous drops in analyst coverage. While these approaches are different from our previous analyses, they are the most natural approaches to use to directly compare the effects of changes in firm and industry analyst competition. We employ two measures of changes in analyst competition, one for the direct change in the analyst coverage at the firm level (i.e., change in firm-level analyst competition as in Hong and Kacperczyk (2010)) and one for changes in analyst competition in the industry in which the firm operates (i.e., indirect changes in analysts following the same industry, but not directly covering the firm of interest).

We conduct these analyses using firm-year observations that were aggregated in the industry analysis from 1990 to 2010. We require that firm-years have data from CRSP, Compustat, and I/B/E/S sufficient to construct the variables used in the regression analysis. Consistent with Hong and Kacperczyk (2010), we construct measures of consensus analyst forecasts using the average of each analyst's most recent forecast of annual earnings for each firm-year. We then construct firm-level measures of accuracy and bias by calculating the difference between the consensus forecasts and actual earnings and scaling by price. While Hong and Kacperczyk (2010) only consider bias, we extend their analyses with the addition of forecast accuracy.

For the OLS analyses, we calculate the number of analysts following each firm and the number of analysts covering each firm's industry. We lag these coverage measures and include lagged control variables following Hong and Kacperczyk (2010). We also include year fixed effects, but not industry effects as the industry analyst coverage measures are likely to be persistent across industries over time. Panel A of Table X reports the results of estimating annual OLS regressions for both forecast bias and absolute forecast error. In column (1), we consider the association between firm-level and industry-level analyst coverage and analyst forecast bias. The coefficients on both of these measures are negative and statistically significant, suggesting that analyst consensus bias at the firm level is negatively related to analyst coverage at both the firm and the industry levels. In column (2), we examine how these variables relate to analyst absolute forecast error (i.e., accuracy). We find that the coefficients on both analyst coverage measures are negative and statically significant, consistent with both firm and industry analyst coverage being associated with higher forecast accuracy. While the coefficients on analyst coverage at the firm and

Table X

The Effect of Analyst Following on Forecast Quality at the Firm Level

This table presents the results of firm-level analyses following the methodology of Hong and Kacperczyk (2010). Panel A presents the results based on OLS regressions. *FirmCoverage* is defined as the number of analysts covering the firm. *IndustryCoverage* is the number of analysts covering the firm's industry. *Size* is the market capitalization, *BM* is the book-to-market ratio, *Profitability* is the ratio of earnings to total assets, *Std. Profitability* is the standard deviation of *Profitability* over the past three years, *Return Volatility* is the standard deviation of daily returns over the past year, and *Ret Annual* is the average monthly return over the past year. All independent variables are lagged one period. *t*-statistics, presented in parentheses, are based on heteroskedasticity-adjusted standard errors that are clustered by firm. Panel B presents the results of a difference-in-differences analysis. Firm-level drops involve firms that experienced analyst drops that were directly related to their analyst following. Industry-level drops involve firms that experienced analyst drops in their industry that did not relate directly to their analyst following. Control firms are matched based on market capitalization, book-to-market, past returns, and analyst coverage. Standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: OLS

	DV = Accuracy (1)	DV = Bias (2)
FirmCoverage	−0.0133***	−0.0092***
	(−11.82)	(−9.52)
IndustryCoverage	−0.0003***	−0.0002***
	(−7.13)	(−3.68)
Log(Size)	−0.0206***	−0.0325***
	(−2.66)	(−4.68)
Log(BM)	0.3018***	0.1134***
	(18.13)	(8.21)
Profitability	−0.3012**	−0.1182*
	(−1.99)	(−1.95)
Std. Profitability	0.0613*	0.0413***
	(1.93)	(3.28)
Return Volatility	29.0622***	16.9571***
	(31.37)	(20.69)
Ret Annual	−4.5863***	−3.7480***
	(−22.16)	(−17.75)
Constant	1.3708***	1.0087***
	(22.69)	(17.11)
Year Fixed Effects	Yes	Yes
Observations	59,577	59,577
R^2	0.133	0.060

Panel B: Difference-in-Differences Analysis

	ΔCoverage	ΔAccuracy	DID	ΔBias	DID
Firm-level drops	−1.170***	0.0017**	0.0010	0.0023**	0.0022**
(n = 382)	(0.227)	(0.0008)	(0.0010)	(0.0009)	(0.0011)
Industry-level drops	−0.149***	0.0029***	0.0019***	0.0018***	0.0015***
(n = 32,134)	(0.018)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Both firm-level and industry-level drops	−1.098***	0.0017***	0.0011*	0.0004	0.0006
(n = 1,398)	(0.117)	(0.0004)	(0.0006)	(0.0005)	(0.0006)

industry levels are statistically negative in both regressions, the coefficients on firm-level coverage are more economically significant and statistically different from those on industry-level coverage in both the accuracy ($F = 131.94$, $p < 0.01$) and bias ($F = 87.20$, $p < 0.01$) regressions.

We further examine these results based on a matched DID approach using brokerage mergers and closures as exogenous drops in analyst coverage. We create treatment groups composed of firms that experienced a firm-level drop in analyst following, an industry-level drop, or both, where industry-level drops include only indirect changes that do not directly relate to firm-specific coverage. Similar to Hong and Kacperczyk (2010), we match control firms to each of these groups each firm-year based on market capitalization, book-to-market, annual stock returns, and level of analyst coverage. Matched control firms must be in the same tercile as a treatment firm for all of these metrics. These analyses allow us to explicitly compare firms with similar characteristics, but that differ in terms of having drops in analyst coverage (at the firm or industry level). They also provide additional support for the identification of our results using a different empirical approach.

We replicate Hong and Kacperczyk's (2010) DID methodology and calculate the consensus bias and accuracy for each firm before and after the date of the analyst drops based on the individual analysts' forecasts with the shortest possible time difference from the drops. We then construct a DID estimate as the change in the differences between the treatment group and the control group. We also provide statistics regarding the change in coverage, bias, and accuracy for the treatment firms. This information is provided in Panel B of Table X.

Several interesting results emerge. First, as expected given the nature of the drops, firms that experience drops that are directly related to the analysts that cover them lose 1.17 analysts on average, while firms that experience drops that are related to analysts covering industry peers lose 0.15 analysts on average (i.e., indirect drops in analyst coverage). In terms of our earlier example, when Mr. Zimits leaves the communication industry as a result of a broker merger, the firms he covers should lose about one analyst on average (i.e., him) while other industry firms would not lose any analysts. Firms experiencing both industry-level and firm-level drops at the same time experience a decrease of about 1.10 analysts, which is roughly the same as that of firms that experience only direct analyst coverage drops.

Starting with the analysis at the firm level, we find that firm-level drops are associated with an increase in bias and that this result continues to hold using the DID estimator (in line with Hong and Kacperczyk (2010)). While Hong and Kacperczyk (2010) do not analyze the impact of the change in the number of analysts on accuracy, we extend their analysis at the firm level by documenting that firm-level drops are also associated with an increase in absolute forecast error. Taken together, when a firm loses an analyst, the bias in the forecast error of the remaining analysts increases and the accuracy of their forecast decreases, consistent with firm-level drops affecting analysts' forecasting effort due to a change in analyst competition.

Perhaps more important for the purposes of our study, we find that industry-level drops are also associated with an increase in bias and absolute forecast error. In reference to our example case, when Mr. Zimits leaves the communication industry, the average analyst forecast bias increases and average forecast accuracy decreases for the firms he did not cover in that industry. Thus, the results from both OLS and the DID analyses suggest that industry-level drops do indeed affect forecast accuracy and bias incrementally to the effects documented by Hong and Kacperczyk (2010). While the results are economically modest (between 10 and 20 bps, on average), they are similar in magnitude to those at the firm level. We note that caution must be exercised when comparing these results across the two groups due to the significant differences in sample size between the two groups as well as differences in the process underlying the effects.

Overall, these results help provide insights on how industry-level drops affect the analyst reports of individual firms. However, these estimates do not capture the complete spillover effects resulting from industry-level analyst drops because they do not aggregate these effects for all firms in an industry, and thus these results cannot be compared to the industry-level results provided in the other tests above because the unit of observation and empirical approaches are different.

IV. Conclusion

We provide the first examination of sell-side analysts as a collective group in financial markets. We examine changes in the scope of the sell-side analyst industry and their impact on capital markets. We document significant variation in the total number of sell-side analysts over time and show that this variation relates to economic factors including market returns, trading volume, brokerage profits, IPO activity, and regulatory changes. More importantly, we find that changes in the number of analysts covering an industry impact the overall quality of analyst forecasts and the flow of information to market participants. We argue that these results are driven by changes in analyst industry competition. We find that the effects of industry analyst changes are more significant for industries with lower quality information environments and for changes in analysts that relate to more knowledgeable analysts. Overall, we demonstrate that having more financial analysts improves information quality and can lead to more efficient dissemination of information.

Our study offers important implications for the academic literature examining sell-side equity analysts. While prior studies generally examine analyst activities at the firm level, we provide new evidence documenting the importance of sell-side equity analysts as a collective industry. We demonstrate that industry-level competition is a distinct force in the sell-side equity analyst industry that plays an important role in influencing analyst behavior. Our findings suggest that, when there is less competitive pressure, analysts exert less effort and consequently produce lower quality reports. Our findings also inform prior studies that often question the economic value of sell-side equity analysts. Taken together, our results suggest that sell-side equity analysts add value to capital markets by alleviating information asymmetries and disseminating information to capital market participants more rapidly and efficiently.

Our results are also relevant to regulators and practitioners. Our findings suggest that analysts play a role in promoting market efficiency in modern capital markets. Regulation aimed at curbing analyst incentives (e.g., Global Settlement) can have potentially unintended consequences if it limits the scope of sell-side analyst industry activities. In addition, our results indicate that recent efforts by large investment banks to downsize their sell-side analyst staff can have negative externalities for other market participants.

Initial submission: May 4, 2015; Accepted: May 4, 2016
Editors: Bruno Biais, Michael R. Roberts, and Kenneth J. Singleton

Appendix A: Variable Definitions

- *Returns*: Value-weighted industry portfolio monthly returns based on firms' prior month market-value weight in the industry.
- *Number of IPOs*: The number of completed offerings in the industry group over the past month. We exclude IPOs with an offer price below $5 per share, ADRs, and IPOs not listed on CRSP within 30 days of the issuance date.
- *Net Delistings*: The difference between the number of IPOs and the change in listed firms in the industry (obtained from CRSP) over the past month.
- Δ*Trading Volume*: The monthly change in industry trading volume. Industry trading volume is the sum of all firms' trading volume (in number of shares) over the past month. We use the adjustment algorithm in Gao and Ritter (2010) to adjust trading volume for Nasdaq stocks.
- Δ*Volatility*: The monthly change in volatility, where volatility is the standard deviation of the industry value-weighted daily returns over the past month.
- Δ*Broker Profits*: The monthly change in broker profits. Broker profits is the sum of quarterly net income for all firms in GICS Sub-Industry 40203020 (Investment Banking & Brokerage), spread evenly across each month within the quarter. More specifically, we require firms to mention "investment bank," "brokerage," "broker-dealer," "research," "institutional clients," "institutional trading," "institutional customers," "capital markets," "equity and fixed income," "trading," "underwriting," "initial public offering," "secondary offering," or "securities" in their business description in Compustat.
- Δ*CFNAI*: The monthly change in the Chicago Fed National Activity Index (CFNAI), obtained from the Federal Reserve Bank of Chicago.
- *Reg FD*: The nine-month period beginning October 1, 2000 and ending July 1, 2001.

- *Global Settlement*: The nine-month period beginning October 1, 2001 and ending July 1, 2002.
- *SOX*: The nine-month period beginning July 1, 2002 and ending April 1, 2003.
- Δ*Cost per MB*: The monthly change in the cost per megabyte of data in the United States based on new computer prices.
- Δ*Inst. Holdings*: The monthly change in the dollar value of aggregate industry value owned by institutional investors based on 13F filings.
- Δ*Net Insider Trading*: The change in average net insider trading, averaged across all firms in an industry group. Net insider trading is the number of buy shares less the number of sell shares, scaled by the sum of the number of buy shares and the number of sell shares.
- Δ*Short Interest*: Short interest scaled by shares outstanding, averaged across all firms in an industry group.
- *Size*: The natural log of one plus quarterly assets, averaged across all firms in an industry group.
- *Profitability*: Quarterly profit scaled by quarterly total assets, averaged across all firms in an industry group.
- *Absolute Change in Profitability*: The absolute value of the quarter-over-quarter difference in *Profitability*.
- *Sales Growth*: Percentage change in sales, averaged across all firms in an industry group.
- *Analyst Experience*: Average number of months of firm experience for all analysts covering firms in the industry.
- *Market to Book*: Price times shares outstanding, scaled by quarterly equity and averaged across all firms in an industry group.
- *%Analyst Participation*: The percentage of analysts in an industry who were considered active analysts in period $t-2$ and provide at least one report in period t after a drop in industry analysts occurs in period $t-1$. If any analyst is dropped in period $t-1$, the analyst in not considered in either the numerator or denominator of the ratio.
- *%Recommendations*: The percentage of analysts in an industry who were considered active analysts in period $t-2$ and provide at least one recommendation in period t.
- *Forecasts per Analysts*: The number of reports provided by analysts in an industry who provide at least one report in period t divided by the number of analysts who were considered active analysts in period $t-2$.
- *Report Timing*: The number of days between the end of period $t-1$ and the first report made by analysts in the subsequent three months.
- *%Previous_Firms*: The ratio of the number of nondropped firms that were actively covered in $t-2$ and received at least one report in t, divided by the number of nondropped firms who were actively covered in $t-2$.

- *%New_Firms*: The ratio of the number of new firms that were not actively covered in $t - 2$ and received at least one report in t, divided by the number of nondropped firms that were actively covered in $t - 2$.
- *Question_Length*: The average length of the questions asked by analysts in conference calls that took place during the three months following a drop (i.e., t, $t + 1$, and $t + 2$), calculated as the ratio of the number of words spoken by analysts in the call divided by the number of questions asked.
- *Information Convergence*: The industry average of firms' standard deviation of analyst forecasts divided by stock price.

Appendix B
Firms Affected by Analyst Drops by Industry

This table provides descriptive information on the average firms affected by analyst drops by industry group (GGROUP) based on the 24 GICS Industry Groups. % Firm Dropped is the percentage of firms from that industry affected by drops, on average. % MCAP dropped is the percentage of an industry's market capitalization affected by drops, on average.

GGROUP	Industry	% Firm Dropped	% MCAP Dropped
1010	Energy	6.5%	25.3%
1510	Materials	3.7%	10.1%
2010	Capital goods	2.6%	10.7%
2020	Commercial and professional services	2.6%	6.0%
2030	Transportation	7.0%	13.2%
2510	Automobiles and components	6.5%	22.2%
2520	Consumer durables and apparel	3.4%	9.0%
2530	Consumer services	5.7%	13.6%
2540	Media	6.5%	16.8%
2550	Retailing	4.2%	9.5%
3010	Food and staples retailing	10.4%	19.1%
3020	Food, beverage, and tobacco	9.7%	27.4%
3030	Household and personal products	11.0%	30.8%
3510	Health care equipment and services	3.5%	11.0%
3520	Pharmaceuticals, biotechnology, and life sciences	4.6%	29.2%
4010	Banks	3.3%	11.9%
4020	Diversified financials	5.3%	9.9%
4030	Insurance	7.0%	14.2%
4040	Real estate	6.1%	6.6%
4510	Software and services	3.2%	14.6%
4520	Technology hardware and equipment	3.5%	13.0%
4530	Semiconductors and semiconductor equipment	10.5%	31.6%
5010	Telecommunication services	9.6%	27.3%
5510	Utilities	10.8%	16.9%
Overall		5.4%	15.3%

Appendix C
Descriptive Statistics for Tests Involving Analyst Drops

	Mean	*SD*	Q1	Median	Q3
Main DV					
Accuracy	0.402	0.217	0.244	0.372	0.518
Bias	0.235	0.211	0.080	0.207	0.348
Controls					
Size	5.289	1.195	4.413	5.092	6.060
Profitability	−0.152	0.410	−0.136	−0.031	−0.005
Sales Growth	−0.282	0.729	−0.233	−0.074	0.001
Analyst Experience	38.227	11.117	30.161	37.997	44.841
Market to Book	3.386	6.780	1.409	2.289	4.032
Absolute ΔProfitability	0.070	0.252	0.001	0.004	0.019
Other DVs					
Dispersion	0.018	0.019	0.005	0.011	0.023
%Analyst Participation	0.465	0.099	0.402	0.469	0.532
Forecasts per Analyst	2.048	1.290	1.184	1.747	2.509
%Recommendations	0.158	0.060	0.117	0.154	0.194
Report Timing	30.853	6.299	26.430	30.077	34.940
%Previous Firms	0.640	0.121	0.569	0.653	0.725
%New Firms	0.019	0.024	0.005	0.014	0.025
Question Length	47.325	7.630	42.720	46.252	49.889
Information Convergence	0.018	0.019	0.005	0.011	0.023
AnalystInfo	0.123	0.033	0.100	0.119	0.142
EAInfo	0.096	0.043	0.069	0.090	0.116

REFERENCES

Admati, Anat R., and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3–40.

Adrian, Tobias, Erkko Etula, and Tyler Muir, 2014, Financial intermediaries and the cross-section of asset returns, *Journal of Finance* 69, 2557–2596.

Allee, Kristian D., and Matthew D. DeAngelis, 2015, The structure of voluntary disclosure narratives: Evidence from tone dispersion, *Journal of Accounting Research* 53, 241–274.

Altinkilic, Oya, Vadim S. Balashov, and Robert S. Hansen, 2013, Are analysts' forecasts informative to the general public? *Management Science* 59, 2550–2565.

Altinkilic, Oya, and Robert S. Hansen, 2009, On the information role of stock recommendation revisions, *Journal of Accounting and Economics* 48, 17–36.

Asquith, Paul, Michael B. Mikhail, and Andrea S. Au, 2005, Information content of equity analyst reports, *Journal of Financial Economics* 75, 245–282.

Bai, Jennie, Thomas Philippon, and Alex Savov, 2015, Have financial markets become more informative? Working paper, Georgetown University and New York University.

Bailey, Warren, Haitao Li, Connie X. Mao, and Rui Zhong, 2003, Regulation fair disclosure and earnings information: Market, analysts, and corporate responses, *Journal of Finance* 58, 2487–2514.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645–1680.

Balakrishnan, Karthik, Mary B. Billings, Bryan Kelly, and Alexander Ljungqvist, 2014, Shaping liquidity: On the causal effects of voluntary disclosure, *Journal of Finance* 69, 2237–2278.

Besley, Timohty, and Andrea Prat, 2006, Handcuffs for the grabbing hand? Media capture and government accountability, *American Economic Review* 96, 720–736.

Bhojraj, Sanjeev, Charles Lee, and Derek K. Oler, 2003, What's my line? A comparison of industry classification schemes for capital market research, *Journal of Accounting Research* 41, 745–774.

Boni, Leslie, and Kent L. Womack, 2006, Analysts, industries, and price momentum, *Journal of Financial and Quantitative Analysis* 41, 85–109.

Bowen, Robert M., Angela K. Davis, and Dawn A. Matsumoto, 2002, Do conference calls affect analysts' forecasts? *The Accounting Review* 77, 285–316.

Bradley, Daniel, Jonathan Clarke, Suzanne Lee, and Chayawat Ornthanalai, 2014, Are analysts' recommendations informative? Intraday evidence on the impact of time stamp delays, *Journal of Finance* 69, 645–673.

Bushman, Robert, Joseph D. Piotroski, and Abbie J. Smith, 2005, Insider trading restrictions and analysts' incentives to follow firms, *Journal of Finance* 60, 35–66.

Chen, Hsuan-Chi, and Jay R. Ritter, 2000, The seven percent solution, *Journal of Finance* 55, 1105–1131.

Chen, Xia, Qiang Cheng, and Kin Lo, 2010, On the relationship between analyst reports and corporate disclosures: Exploring the roles of information discovery and interpretation, *Journal of Accounting and Economics* 49, 206–226.

Clement, Michael B., 1999, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? *Journal of Accounting and Economics* 27, 285–303.

Clement, Michael B., Jeffrey Hales, and Yanfeng Xue, 2011, Understanding analysts' use of stock returns and other analysts' revisions when forecasting earnings, *Journal of Accounting and Economics* 51, 279–299.

Cohen, Lauren, Dong Lou, and Christopher Malloy, 2012, Casting conference calls, Working paper, Harvard Business School and London School of Economics.

Cooper, Rick A., Theodore E. Day, and Craim M. Lewis, 2001, Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics* 61, 383–416.

DellaVigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and Friday earnings announcements, *Journal of Finance* 64, 709–749.

Derrien, François, and Ambrus Kecskés, 2013, The real effects of financial shocks: Evidence from exogenous changes in analyst coverage, *Journal of Finance* 68, 1407–1440.

Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113–2141.

Fong, Kingsley Y. L., Harrison G. Hong, Marcin T. Kacperczyk, and Jeffery D. Kubik, 2014, Do security analysts disciple credit rating agencies? Working paper, Princeton University.

Francis, Jennifer, Katherine Schipper, and Linda Vincent, 2002, Expanded disclosures and the increased usefulness of earnings announcements, *The Accounting Review* 77, 515–546.

Frankel, Richard, S. P. Kothari, and Joseph Weber, 2006, Determinants of the informativeness of analyst research, *Journal of Accounting and Economics* 41, 29–54.

Gao, Xiaohui, and Jay R. Ritter, 2010, The marketing of seasoned equity offerings, *Journal of Financial Economics* 97, 33–52.

Gentzkow, Matthew, and Jesse M. Shapiro, 2006, Media bias and reputation, *Journal of Political Economy* 114, 280–316.

Greene, William H., 2003, *Econometric Analysis* (Pearson Education, Upper Saddle River, NJ).

Greenwood, Robin, and David Scharfstein, 2013, The growth of finance, *Journal of Economic Perspectives* 27, 3–28.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393–408.

Groysberg, Boris, Paul M. Healy, and David A. Maber, 2011, What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research* 49, 969–1000.

Hauswald, Robert, and Robert Marquez, 2003, Information technology and financial services competition, *Review of Financial Studies* 16, 921–948.

Hauswald, Robert, and Robert Marquez, 2006, Competition and strategic information acquisition in credit markets, *Review of Financial Studies* 19, 967–1000.

Hirshleifer, David, Kewei Hou, and Siew Hong Teoh, 2009, Accruals, cash flows, and aggregate stock returns, *Journal of Financial Economics* 91, 389–406.

Holzer, Harry J., Lawrence F. Katz, and Alan B. Krueger, 1991, Job queues and wages, *Quarterly Journal of Economics* 106, 739–768.

Hong, Harrison, and Marcin Kacperczyk, 2010, Competition and bias, *Quarterly Journal of Economics* 125, 1683–1725.

Hong, Harrison, and Jeffrey D. Kubik, 2003, Analyzing the analysts: Career concerns and biased earnings forecasts, *Journal of Finance* 58, 313–351.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Howe, John S., Emre Unlu, and Xuemin Sterling Yan, 2009, The predictive content of aggregate analyst recommendations, *Journal of Accounting Research* 47, 799–821.

Hribar, Paul, and John McInnis, 2012, Investor sentiment and analysts' earnings forecast errors, *Management Science* 58, 293–307.

Jacob, John, Thomas Z. Lys, and Margaret A. Neale, 1999, Expertise in forecasting performance of security analysts, *Journal of Accounting and Economics* 28, 51–82.

Jegadeesh, Narasimhan, Joonghyuk Kim, Susan D. Krische, and Charles Lee, 2004, Analyzing the analysts: When do recommendations add value? *Journal of Finance* 59, 1083–1124.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2009, Conflicts of interest and stock recommendations: The effects of the global settlement and related regulations, *Review of Financial Studies* 22, 4189–4217.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2012, Analysts' industry expertise, *Journal of Accounting and Economics* 54, 95–120.

Kahneman, Daniel, and Dan Lovallo, 1993, Timid choices and bold forecasts: A cognitive perspective on risk taking, *Management Science* 39, 17–31.

Kelly, Bryan, and Alexander Ljungqvist, 2012, Testing asymmetric-information asset pricing models, *Review of Financial Studies* 25, 1366–1413.

Kilduff, Gavin J., Hillary Anger Elfenbein, and Barry M. Staw, 2010, The psychology of rivalry: A relationally dependent analysis of competition, *Academy of Management Journal* 53, 943–969.

Kothari, S. P., Jonathan Lewellen, and Jerold B. Warner, 2006, Stock returns, aggregate earnings surprises, and behavioral finance, *Journal of Financial Economics* 79, 537–568.

Lehavy, Reuven, Feng Li, and Kenneth Merkley, 2011, The effect of annual report readability on analyst following and the properties of their earnings forecasts, *The Accounting Review* 86, 1087–1115.

Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Wei, and Hong Yan, 2007, Conflicts of interest in sell-side research and the moderating role of institutional investors, *Journal of Financial Economics* 85, 420–456.

Ljungqvist, Alexander, Felicia Marston, and William J. Wilhelm, 2006, Competing for securities underwriting mandates: Banking relationships and analyst recommendations, *Journal of Finance* 61, 301–340.

Loh, Roger K., and René M. Stulz, 2011, When are analyst recommendation changes influential? *Review of Financial Studies* 24, 593–627.

Loh, Roger K., and René M. Stulz, 2014, Is sell-side research more valuable in bad times? National Bureau of Economic Research Paper No. w19778.

Loughran, Tim, and Bill McDonald, 2014, Measuring readability in financial disclosures, *Journal of Finance* 69, 1643–1671.

Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen, 2011, What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions, *The Accounting Review* 86, 1383–1414.

Mayew, William J., 2008, Evidence of management discrimination among analysts during earnings conference calls, *Journal of Accounting Research* 46, 627–659.

Michaely, Roni, and Kent L. Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, *Review of Financial Studies* 12, 653–686.

Mikhail, Michael B., Beverly R. Walther, and Richard H. Willis, 1999, Does forecast accuracy matter to security analysts? *The Accounting Review* 74, 185–200.

Moen, Espen R., 1999, Education, ranking, and competition for jobs, *Journal of Labor Economics* 17, 694–723.

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215–260.

Morrison, Steven A., and Clifford Winston, 1990, The dynamics of airline pricing and competition, *The American Economic Review* 80, 389–393.

Nickell, Stephen J., 1996, Competition and corporate performance, *Journal of Political Economy* 104, 724–746.

Papina, Jessica, Laid-off sell-side analysts weigh options outside research, Dow Jones Newswires, June 25, 2009.

Philippon, Thomas, 2015, Has the U.S. finance industry become less efficient? On the theory and measurement of financial intermediation, *American Economic Review* 105, 1408–1438.

Reingold, Dan, 2006, *Confessions of a Wall Street Analyst* (HarperCollins, New York).

Rogers, Jonathan L., and Andrew Van Buskirk, 2013, Bundled forecasts in empirical accounting research, *Journal of Accounting and Economics* 55, 43–65.

Segal, Julie, Death of the IPO, Institutional Investor Magazine, October 13, 2010.

Stickel, Scott E., 1992, Reputation and performance among security analysts, *Journal of Finance* 47, 1811–1836.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value? *Journal of Finance* 51, 137–167.

Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.