Does the scope of the sell-side analyst industry matter? An examination of bias, accuracy and information content of analyst reports

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ABSTRACT

This paper examines factors related to changes in the scope of the sell-side analyst industry and whether such changes affect the quality of analyst reports as well as how information is impounded into prices. We find that factors commonly associated with economic and financial market growth and profitability within the financial services industry are positively associated with growth in the analyst industry. We also find evidence of a differential growth pattern for analysts that work for investment banks compared with those that do not based on a quasi-natural experiment using changes in financial regulations. Furthermore, increased analyst presence results in better functioning markets across several dimensions: forecasts are more accurate and less biased, and their information is impounded into prices faster. These results are consistent using both standard regression analysis and quasi-natural experiments that attempt to examine causality more precisely. Overall, the findings suggest that analysts provide positive externalities to financial markets.

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I. Introduction

Sell-side financial analysts as a whole play an important role in the U.S. capital markets. Analysts facilitate the distribution of financial information and their reports, earnings forecasts, and recommendations provide valuable information to market participants (Kadan, Madureira, Wang, and Zach (2009); Loh and Stulz (2011)). Further, analysts help shape capital markets through their interactions with underwriters, brokers, institutional investors, and management. Analyst activities are of particular interest to investors, regulators, and the financial press and significant regulatory changes have been enacted over the past decade to preserve the integrity of analysts' research as well as their interactions with other key financial market participants (e.g., Reg FD, Global Settlement, NASD Rule 2711, NYSE Rule 472). Despite the broad interest in the role of sell-side analysts, our understanding of the overall factors related to changes in the scope of the analyst-industry as a whole and the economic consequences of these changes is limited.

In this study we focus on two basic questions. First, what are the factors that relate to, and perhaps affect, the overall scope of the sell-side analyst industry over time? That is, what economy-wide and industry-wide factors affect the scope of the industry and in particular, the number of analysts that are employed in the sell-side industry? As we elaborate below, we find that factors commonly associated with economic and financial market growth and profitability within the financial services industry are positively associated with growth in the analyst industry. The evidence also suggests a differential growth pattern for analysts that work for investment banks compared with those that do not.

Our second question goes one step further and investigates how the size of the sell-side analyst industry affects the manner in which information is impounded into prices. We examine how changes in the total number of analysts affect how information is disseminated in financial markets and the aggregate accuracy and bias in the forecasts analysts produce. Our results suggest that increases in the number of analysts result in better and faster information dissemination. Further, we find that existing analysts in the industry issue forecasts that are more accurate, and less biased as more analysts enter the industry. Information in analyst reports is also impounded into prices faster, not only for individual stocks, but for the market as a whole as the number of analysts increases. These results are consistent using both standard regression analysis and quasi-natural experiments that attempt to examine causality more precisely. The issues we address in this paper are relevant not only to the corporations and to the brokerage houses that employ analysts, but also to policy makers and regulatory bodies. The findings suggest that at least along the dimensions investigated here, analysts provide positive externalities to financial markets.

Using several proxies for industry scope, we first document how changes in the overall scope of the sell-side analyst industry are related to, and affected by overall economic conditions (our primary estimate of the industry scope is the number of analysts employed; but we also use several other measures). Standard economic analysis suggests that the number of analysts employed depends on the marginal value they bring to the brokerage houses that employ them. Since analysts rarely generate direct profits, it is difficult to directly capture the costs and benefits of analysts research to their employers (e.g., Michaely and Womack (1999); Jegadeesh, Kim, Krische, and Lee (2004) Bradley, Jordan, and Ritter (2008)). As such, we use several factors that are likely to affect their profitability; either because the industry is pro-cyclical or because the level of employment depends on revenue drivers such as IPOs, commissions form trading volume or profitability of the industry. Therefore we expect that aggregate market capitalization, number of listed firms, IPO activity, trading volume, overall economic activity, and financial services industry profitability are associated with (and perhaps affect) the overall profitability of the sell-side analyst industry.

We conduct our first set of analyses by examining both levels and changes in our proxies for the sell-side industry scope at the market and the industry level. The market level is a natural starting point because it allows us to examine the scope of the industry more broadly without assuming any specific grouping scheme. Recent studies, however, emphasize that brokers tend to organize their efforts by specific industries, suggesting that brokers likely make resource allocation decisions by industry (Boni and Womack (2006); Kadan, Madureira, Wang, and Zach (2012)). In addition, industry analyses likely capture greater variation in analyst activity, because they allow industries to exhibit different trends. For example, analyses at the market level would not identify much variation in the total number of analysts if the analyst activity in some industries is expanding while at the same time contracting in others. Furthermore, market level analyses require a time-series methodology that suffers from well-known econometric problems (e.g., serially correlated residuals, non-stationarity issues, etc.). In light of these trade-offs, we conduct our analysis at both the market and the industry level.

Across both the market and industry levels, our results provide consistent evidence that aggregate returns and IPO activity are positively related to changes in the number of analysts. Further, at the industry level, we also find strong evidence suggesting that trading volume is an important determinant of analyst presence. Our results are also similar using alternative measures of scope of analyst activities including changes in the number of brokers and changes in number of firms covered by analysts. Overall, our findings suggest that increases in the scope of the analyst industry are correlated with economic conditions that are expected to generate higher analyst profits. Importantly, these findings also shed light on the factors that determine entry in the financial services industry and also relate to studies examining entry in other industries (Ellis, Michaely, and O'Hara (2002), Barrot (2013)).

Interestingly, we also find evidence suggesting that investment banks' employment of analysts exhibits greater sensitivity to market conditions and particularly to changes in IPO activity relative to other brokerage houses. We further explore this finding by taking advantage of a semi-natural experiment that allows us to examine whether profits from IPO activity affect the scope of the sell-side industry. Using a difference-in-difference analysis, we find that the Global Settlement, which cut the ties between investment banking fees and analysts' compensation, had a significantly greater reduction in employment in banks with IPO activities. Economically, these brokers reduced the number of analysts employed by twelve more analysts per year, on average, than other brokers in the three years following the regulation. Further, relative to other brokerage firms, investment banks not only reduced the number of analysts they employed but also significantly reduced the number of firms they cover. These results provide further evidence in support of our findings that changes in the number of aggregate analysts depend on factors related to the expected profits of analyst-related activities.

Analysts are one of the most influential sources of information in capital markets and, naturally, one would expect that changes in the overall number of analysts could have an impact on analysts' behavior and the stock market information environment. Increasing the number of analysts presumably increases the amount of information impounded in prices (Grossman and Stiglitz (1980); Hong, Lim, and Stein (2000b); Chan and Hameed (2006)) and increases competition among analysts thereby reducing the extent of bias (Hong and Kacperczyk (2010)) and increasing accuracy. On the other hand, new entering analysts may be less experienced and provide less accurate forecasts and recommendations.[1] Accordingly, we examine whether changes in the overall number of analysts affect aggregate measures of the accuracy, bias, and informativeness of analyst reports, where informativeness is measured by magnitude of their association with stock returns.

To ensure that our analysis at the aggregate level does not simply capture improvements in information related to the number of analyst covering individual firms, we remove individual firm observations that experience direct changes in analyst coverage before calculating the aggregate variables. In other words, we aggregate our measures for firms where the number of analysts following them does not change, but allow for other analysts to enter or exit these firms' industry. Thus, we consider effects that are incremental to the firm-level effects documented in prior studies (e.g., Hong and Kacperczyk (2010)). We conduct these analyses using a standard regression framework as well as using a natural experiment to identify exogenous changes in aggregate analyst following based on brokerage house mergers and closures.

We find that increases in the number of analysts providing forecasts are associated with lower aggregate forecast errors and less aggregate optimistic bias; and decreases in the number of analysts are associated with higher forecast errors and more optimistic bias. Specifically, we find that a drop in one analyst covering an industry, based on changes in analysts from brokerage house mergers and closures, results in a 2.9% increase in aggregate forecast error and a 2.7% increase in optimistic bias. These findings suggest that having a larger sell-side analyst presence improves the quality of analyst reports. These findings also hold when we use all changes in the total number of analysts in an OLS regression with industry fixed effects rather than those from the natural experiment.

In addition, we find that the total number of analysts is positively related to the average informativeness of analyst forecasts, and negatively related to the average informativeness of earnings announcements. That is, an increase in the number of analysts speeds the information flow so that more of the information is revealed through analysts' revisions of earnings prior to the actual earnings announcement. Indeed the market seems less surprised by the earning announcements themselves when more analysts follow the industry. Thus, changes in the overall number of analysts have important consequences for the quality of analyst forecasts and the aggregate information environment.

[1] Hong, Kubik, and Solomon (2000a) provide empirical evidence that inexperienced analysts are less likely to provide innovative forecasts, issue less timely forecasts, and revise their forecasts more frequently.

Prior studies generally examine analysts' activities at the firm level to assess why analysts cover particular firms and how their coverage decisions influence the quality of individual firms' information environments (e.g., Hong and Kacperczyk (2010);Derrien and Kecskés (2013)). By using aggregate-level analyses, we are able to address a broader set of questions regarding factors related to changes in the scope of the sell-side analyst industry and the aggregate consequences of these changes. It is important to address these questions at aggregate levels for at least two reasons. First, firm-level analyses may not capture the overall extent of analyst activities in the aggregate. Brokerage houses likely make resource allocation decisions at aggregate levels such as by industry (Kadan et al. (2012)) before considering firm-level issues and analysts themselves are often evaluated based on their aggregate performance (e.g., Institutional Investors industry rankings). In addition, changes in analyst activities at the firm level do not necessarily capture changes at the aggregate level because analysts often make coverage decisions that do not change the overall level of their activities such as dropping one firm from their portfolio to cover another. Second, it is not necessarily clear ex ante whether the findings of firm-level studies will extend to aggregate analyses. 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 post earnings announcement drift and the accruals anomaly) weaken or even reverse direction (e.g., Kothari, Lewellen, and Warner (2006); Hirshleifer, Hou, and Teoh (2009)). Thus, we extend and complement the findings of firm-level studies by providing evidence that aggregate analyst activities have effects that extend beyond those found at the firm-level.

Our paper also complements recent studies that explore the effects of aggregate analyst outputs such as earnings forecasts and recommendations at both the market and industry levels. Howe, Unlu, and Yan (2009) provide evidence that aggregate analyst recommendations can predict future aggregate returns and earnings. In a similar vein, Hann, Ogneva, and Sapriza (2012) find that, despite the persistent bias in aggregate analyst forecasts, markets continue to fixate on aggregate earnings forecasts and overweight their value in forming expectations about the economy. We complement these findings by providing evidence about the changes in the originators of these reports (i.e., the analysts themselves) and show that increases in the overall number of analysts can improve the quality of the aggregate analyst forecasts and potentially enhance the flow of information.

The remainder of the paper proceeds as follows. Section II introduces the sample and data. Section III provides results regarding the factors associated with the scope of the sell-side analyst industry. In Section IV , we explore the consequences associated with changes in aggregate analyst following and Section V concludes.

II. Data and Sample

We begin our investigation by examining how the analyst industry has evolved over the past two decades. We track analyst activity on a monthly basis using data from analyst reports available on I/B/E/S. Our sample includes about 12.3 million US quarterly and annual EPS forecasts issued between 1989 and 2011 that have sufficient data for industry classification. In order to facilitate tracking analysts and brokers over time, we require each forecast to be associated with a unique analyst and broker code (i.e., we remove anonymous analysts). Our primary proxy for the sell-side industry scope is monthly changes in the overall number of analysts; however, we also consider other measures of analyst activity including the number of brokers, the number of firms with analyst coverage, and number of brokerage houses. We use the analyst codes provided by I/B/E/S to count entering and exiting analysts. We define an entering analyst as any analyst issuing her first forecast in the sample, or who has not issued a forecast in the past 12 months. Similarly, we define an exiting analyst as any analyst issuing her last forecast in the sample, or who does not issue a forecast in the next 12 months. Beginning in 1990, we count the number of new analysts and the number of exiting analysts each month to compute net changes in the number of analysts.

[**Figure 1 about here**]

[**Table I about here**]

Panel A of Table I provides data on the average monthly level and change in the number of analysts, number of brokers, and the number of firms covered by analysts aggregated at the market level. The median number of analysts added to the market each month is 5; and an average of 3.54 additional firms receive new coverage each month. Figure 1 depict the time-series variation in these measures. These figures suggest several interesting trends. First, Figure 1a shows that the number of analysts has been increasing over the past two decades.[2] Throughout the 1990s, the

[2]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

total number of analysts rose steadily from a starting population of around 2,000 to a peak of 3,226 analysts by the end of 1999. In the 2000s, the number of analysts remained relatively steadier, ranging between 2,700 and 3,200 analysts. The figures also depict declines in analyst activity around market downturns, particularly around the recession of the early 1990s, the dot-com bubble in 2001, and the recent Global Financial Crisis in 2007, consistent with analyst presence declining when their services are likely to be less profitable. Recently, the total number of analysts has begun to rise again, consistent with recent projected growth in this industry.[3] It is also important to note that this trend does not appear to be driven simply by changes in how brokerage houses report to I/B/E/S over time, as we see a similar trend emerge in the constant sample of 36 brokers as well as in the other scope variables we examine. For example, Figure 1b shows the number of brokers rising from less than 150 in 1990 to nearly 300 by the end of the sample. Similarly, Figure 1c shows a gradual increase in the percentage of listed firms covered by analysts over time.

To gain more insight as to the source of this trend, we further examine changes in the number of analysts by different broker size groups (Figure 1d). Until the turn of the century, both small and large brokerage houses steadily increased the number of analysts they employed. Interestingly, much of the increase in analyst presence over the last decade, however, appears to be driven by small brokerage houses. Small brokerage houses (that employ less than 10 analysts, on average) appear to be increasing the number of analysts in recent years, in contrast to large brokerage houses (that employ more than 30 analysts, on average) that appear to be decreasing the number of analysts in recent years. In the same vein, Panel B of Table I provides descriptive statistics for the number of analyst based on whether brokers participate in IPO activity and on the size of the broker in terms of the number of analyst employed. These data suggest that analyst activity varies substantially across broker types. In particular, smaller brokerage houses and those that do not participate in investment banking activity tend to employ fewer analysts (only about 3-4 analysts on average). Whereas, the larger brokerages that tend to dominate industry news employ upwards of 50 analysts and several employ over 100. The large number of smaller brokers is partially a

file, these codes generally map to the lead analysts name, however, sometimes they can refer to pairs of analysts or the name of the team (e.g., sector). In untabulated analyses, we find that our inferences are unchanged if we remove observations with names that refer to analyst pairs or sectors.

[3]The United States Department of Labor expects employment of financial analysts to grow 23 percent in the next 10 years due to an increasing demand for understanding complex financial products. `http://www.bls.gov/ooh/business-and-financial/financial-analysts.htm#tab-6`

function of trends in recent years documented in Figure 1d, which shows that analyst activity at smaller brokerages houses has been increasing over the last decade.

More often than not, analysts tend to specialize in particular industries. Prior research suggests that the Global Industry Classification Standard (GICS) provides an accurate representation for how many brokerage houses organize their analyst teams (Boni and Womack (2006),Kadan et al. (2012)). Additionally, other studies suggest that the GICS classification outperforms other classifications (e.g., SIC, NAICS, and Fama-French 48) in terms of its ability to explain stock returns (Bhojraj, Lee, and Oler (2003)). We therefore follow suit and use GICS to classify analysts into industry groups.

The GICS taxonomy consists of 10 sectors, 24 industry groups, 68 industries, and 154 sub-industries.[4] We aggregate our variables across 24 GICS industry groups rather than at the broader sector level or the more detailed industry or sub-industry level because industry groups provide the most consistent level of classification across all analyst firms. As noted in Panel B of Table I, broker size varies significantly across our sample, with some brokers employing as few as three analysts and others employing over 100 analysts. While larger brokers have sufficient resources to employ analysts at a finer level of coverage detail, smaller brokers are more constrained in their coverage decisions and likely staff at a coarser level. Additionally, Kadan et al. (2012) are unable to find any broker that provides consistent coverage across all 68 GICS industries over time. As such, we believe GICS industry groups provide the best choice in terms of understanding both the system by which analysts organize themselves (i.e., GICS) as well as the precision (i.e., level of aggregation) at which analysts aggregate.

[**Figure 2 about here**]

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 and Commercial and Professional Services, attract large numbers of analysts, but are also relatively steady over time (i.e., little change in analysts). Not surprisingly, industries in the Information Technology sector, such as Software and Services and Semiconductors, have exhibited the largest growth in the past

[4] 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 between for these two industry groups between 2002Q4 and 2003Q2 to allow for reclassification of analysts and firms in our sample.

two decades, adding on average 1 new analyst per month.

[Table II about here]

III. The Scope of the Sell-side Analyst Industry Over Time

A. Proxies for Economic and Financial Market Conditions

Standard economic analysis suggests that the total number of analysts depends on the marginal value they bring to the brokers that employ them. It is difficult to directly capture changes in the net value of sell-side analysts to their employers: in most firms analysts do not bring any direct revenue. Rather, investors may reward analysts for their services by directing their trades to the brokerage house. Having quality analysts can also increase the likelihood of the analysts firm landing investment banking deals and increase the prestige of the brokerage house in other less tangible ways.

Due to the lack of direct measures, we consider several proxies that relate to analyst activities and the economic and financial market conditions. First, we expect analyst presence to increase when market value (or aggregate returns) is high. Second, we expect the number of listed firms to relate positively to the number of analysts as it captures both increased demand for analyst services as well as commissions that can be earned from cross-subsidizing research activities with underwriting revenues (Chen and Ritter (2000)). Similarly, we also expect trading volume to be positively related to analyst activity as analysts often receive brokerage and trading commissions (Hayes (1998)). We also control for stock return volatility in our model, although its role is less clear. Volatility is frequently associated with poor market performance, which can lead to lower market activity, but is also related to increased uncertainty which can create higher demand for analyst reports. Finally, we also expect analyst presence to increase during periods of high IPO activity and when brokerage houses are profitable. Examining IPO activity separately also allows us to identify the extent to which the number of listed firms is capturing a source of brokerage house commissions which relate directly to profitability.

To construct these variables, we obtain market data from CRSP, IPO data from Thomson ONE SDC Platinum, accounting variables from Compustat, and macro data from the Chicago Fed. Each of these variables is then measured monthly and aggregated at both the market and

GICS industry level, when feasible.[5] *Market Value* is measured as the sum of the market caps (i.e., price $\times$ shares outstanding) for all listed firms in the market (industry) with available CRSP data. We measure *Returns* as the value-weighted returns from holding the market (industry) portfolio over the past month. Each month, we form value-weighted market (industry) portfolios using firm returns and the prior month's market cap obtained from the CRSP Monthly Return File.[6] Specifically, $Ret_t = \sum_{i=1}^{N} Ret_{i,t} \times \frac{MCAP_{i,t-1}}{\sum_{i=1}^{N} MCAP_{i,t-1}}$ where i denotes firms in the market (industry) group and t denotes month.[7]

The *Number of Listed Firms* is measured by counting the number of actively traded firms (from CRSP). We decompose changes in listed firms into both IPOs and Net Delistings. Using SDC, we measure the *Number of IPOs* as the number of completed offerings in the market (industry) group over the past month (excluding 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* is computed as the difference between the number of IPOs and changes in listed firms.

Consistent with studies that examine the relation between analysts and trading volume at the firm level (Barth, Kasznik, and McNichols (2001)), we compute *Trading Volume* by summing the trading volume (in number of shares) of all firms in the market (industry) over the past month. We measure stock return volatility using value-weighted daily returns over the past 1 month from the CRSP Daily Return File. Each day, we form a value-weighted market (industry) portfolio based on the prior month's end market cap: $Ret_d = \sum_{i=1}^{N} Ret_{i,d} \times \frac{MCAP_{i,t-1}}{\sum_{i=1}^{N} MCAP_{i,t-1}}$ At the end of each month, we compute *Volatility* as the standard deviation of the daily market (industry) portfolio returns over the prior month. We include the Chicago Fed National Activity Index (*Economic Activity*) to capture for macro trends and aggregate income within GICS Group 4020 Diversified Financials (*Broker Income*) to as a gauge for the overall profitability within the financial services industry.[8]

[5] While it is reasonable that brokers may examine horizons longer than one month when determining their hiring decisions, aggregating these variables over longer horizons may alter the underlying concept in many instances. For example, longer horizon returns may capture momentum in addition to being a proxy for an analyst-related profit source (e.g., Jegadeesh and Titman (1993)). Similarly, longer horizon trading volume may represent contrarian signals that stocks are overvalued and may not proxy for analyst-related profits (Lee and Swaminathan (2000)). Thus, we restrict our variables to a one month horizon in order to examine cleaner measures analyst-related profits. However, in untabulated analysis, our results remain significant and in the predicted direction when we examine longer horizons, including both quarterly and annual measures.

[6] We incorporate delistings into monthly data following procedures outlined in Beaver, McNichols, and Price (2007).

[7] Our results are similar if we use equal-weighted returns.

[8] Since income is measured quarterly, we equally divide this measure across the three months within each quarter.

In addition, we include calendar month fixed effects to control for potential seasonal fluctuations in analyst employment that are potentially correlated with financial market factors. We also control for the extent of buy-side analyst activity in many of our analyses using the percentage of aggregate market value owned by institutional investors based on 13-f filings. We do not include this measure in all of our analyses because this data is only available after 1992 which significantly impacts our sample. We expect sell-side analyst activities to be positively related to buy-side activity because buy-side analysts frequently use analyst reports in their decisions (Michaely and Womack (1999)), however, it is also possible that when there are more buy-side analysts there is less demand for analyst reports because the efficiency of market prices is positively related to institutional holdings (Boehmer and Kelley (2009)).

B. Market-level Analysis

What determines the scope of the sell-side analysts industry? Our first analysis examines how our market-wide proxies relate to the total number of analysts at the aggregate level. Specifically we examine how economic and financial market factors in period t relate to the number of analysts in period $t+1$ by estimating the following regression models:

$$\begin{aligned} Analyst_{t+1} = {} & \alpha_0 + \alpha_1 Market\ Value_t + \alpha_2 Number\ of\ Listed\ Firms_t \\ & + \alpha_3 Trading\ Volume_t + \alpha_4 Volatility_t + \alpha_5 Broker\ Profits_t \\ & + \alpha_6 Economic\ Activity_t + \alpha_7 Inst.\ Holdings_t + \sum_m \zeta_m + \epsilon_t \end{aligned} \tag{1}$$

$$\begin{aligned} \Delta Analyst_{t+1} = {} & \beta_0 + \beta_1 Returns_t + \beta_2 \Delta Number\ of\ Listed\ Firms_t \\ & + \beta_3 \Delta Trading\ Volume_t + \beta_4 \Delta Volatility_t + \beta_5 \Delta Broker\ Profits_t \\ & + \beta_6 \Delta Economic\ Activity_t + \beta_7 \Delta Inst.\ Holdings_t + \sum_m \zeta_m + \epsilon_t. \end{aligned} \tag{2}$$

$$\begin{aligned} \Delta Analyst_{t+1} = {} & \delta_0 + \delta_1 Returns_t + \delta_2 Number\ of\ IPOs_t + \delta_3 Net\ Delistings_t \\ & + \delta_4 \Delta Trading\ Volume_t + \delta_5 \Delta Volatility_t + \delta_6 \Delta Broker\ Profits_t \\ & + \delta_7 \Delta Economic\ Activity_t + \delta_8 \Delta Inst.\ Holdings_t + \sum_m \zeta_m + \epsilon_t. \end{aligned} \tag{3}$$

[Table III about here]

Table III, Panel A presents the results from tests based on Equation 1, t-statistics are based on Newey-West standard error correction for four lags. The results from column 1 indicate that

Market Value, *Number of Listed Firms*, and *Broker Profits* are positively and significantly associated with the number of analysts, consistent the with the number of analysts increasing as the market increases in size. We also find that the level of analysts is positively associated with the level of volatility. These results continue to hold after including a proxy for overall economic activity (Column 2) and after augmenting the model with institutional holdings (Column 3).

To strengthen our inferences and reduce the likelihood of spurious correlations, we reproduce the results from Panel A, using a changes specification.[9] Table III, Panel B re-presents the results of estimating the models in Equations 2 and 3. Similar to the level results, changes in the number of analysts are positively and significantly related to *Returns*, Δ*Number of Listed Firms*, and Δ*Broker Profits* (column 1). In addition, after decomposing changes in the *Number of Listed Firms* into *Number of IPOs* and *Net Delistings*, we find that changes in the number of analysts are positively associated with IPO activity. These results are robust to controlling for changes in institutional holdings (Column 4).[10] Overall, these results are consistent with the notion that, in the aggregate, the number of analysts positively varies with the size of the market as well as with IPO activities, suggesting that when broker profits increase, the number of analysts also increases.

In Table III, Panel C we re-examine Equation 3 using other dimensions of analyst scope. In Columns 2-4, we vary ΔAnalyst by scaling it by the overall market capitalization, the number of listed firms, and the number of covered firms, and continue to find that *Returns* and *Broker Profits* are positively and significantly correlated with analyst activity. We observe similar trends in other dimensions of scope. For example, returns are positively associated with increases in the number of brokerage houses in addition to the number of analysts (Column 5). Increases in firm coverage are positively related to IPO activity, overall market return and brokerage profits (Columns 6-7). In untabulated analyses, we also examine these additional scope variables at the industry level, and find that IPO activity and changes in trading volume and positively related to changes in industry analyst following. Taken together, these other dimensions of analyst scope provide consistent evidence that analyst activity expands following periods of economic growth and

[9]The changes specification is also superior from an econometric modeling perspective. In particular, we test each of the explanatory variables in this model for non-stationarity. Both augmented Dickey-Fuller and Phillips-Perron unit-root tests strongly reject the null that any of the variables in the above model contains a unit root ($p<0.01$), thus providing strong evidence that the variables are stationary. This is not the case in the level specification.

[10]In untabulated analysis, we also re-estimate equations 1- 3 including the lagged dependent variable as a control. For the levels models, our results are similar, except that *Broker Profits* and *Number of Listed Firms* are no longer significant. For the changes models, our results are similar, except that *Number of IPOs* is no longer significant.

high IPO activity, strengthening the inferences from the $\Delta Analyst$ results.

C. Industry-level Analysis

While the market-level results provide some insight into what economic forces influence aggregate analyst following, we augment the aggregate market analyses with industry-level analyses. Prior literature indicates that analysts are generally organized along industry lines (Boni and Womack (2006); Kadan et al. (2012)) and decisions regarding analyst activities are frequently made at the industry-level. In addition, the industry-level likely provides significantly more variation in analyst activity because market-level measures cannot detect offsetting movements between industries very well nor can they account for heterogeneity across different industry groups or brokers. For example, consider a scenario in which the Software & Services industry has a high number of IPOs in a particular period and the Real Estate industry has a low number of IPOs. These industries may respond by increasing and decreasing the number of analysts, respectively. However, the overall effect could be small in the overall market in terms of net analysts, even though the period is associated with a high number of IPOs, because the market-level analyses do not consider heterogeneity across industries. Furthermore, the market-level analyses require a time-series methodology that suffers from well-known econometric problems (e.g., serially correlated residuals, non-stationarity issues, etc.).

For our industry tests, we estimate both the level regression (with industry fixed effects) and the change in level regressions using variables based on the 24 GICS Industry Groups. For the level regression, for example, we use the market value of firms in each industry, the number of IPOs and delisted firms in the industry, etc. The only two variables that are not at the industry level are the proxies for broker profits and overall economic activity which are not measured by industry. We also include industry fixed effects in order to control for unobserved constant industry factors that relate to levels and changes in analysts at the industry-level, but are not explicitly controlled for in the models. In all industry tests, standard errors are clustered by both industry and month.

[**Table IV about here**]

Table IV provides the results from these tests. Panel A presents the results based on the level of analysts covering specific industries. The results from column 1 indicate that *Market Value*, *Number of Listed Firms*, and *Trading Volume* are positively and significantly associated with the number of analysts, consistent the with the analysts increasing as industries increase in size and activity. These results continue to hold after controlling the level of *Economic Activity* (column 2) and *Inst. Holdings* (column 3).

Table IV, Panel B presents the results based on a changes specification. Similar to the level results, changes in the number of analysts are positively and significantly related to *Returns* and Δ*Trading Volume*, but *Number of Listed Firms* is no longer significant. However, if we decompose Δ*Number of Listed Firms* into *Number of IPOs* and *Net Delistings*, we find that *Number of IPOs* in an industry is positive and significantly related to the changes in the number of analysts.[11] In terms of statistical and economic significance, *Number of IPOs* also appears to be the most important component in determining changes in the total number of analysts at the industry level. A one standard deviation increase in *Number of IPOs* in an industry results in about one new analyst per industry-month (i.e., $2.387 \times 0.4298 = 1.03$).

Our industry results suggest that there is important heterogeneity across industry groups that is not captured in the market-level results. Consider, for example, the effect of IPOs on changes in analysts. In the market regressions, the sensitivity of Δ*Analyst* within the market to market IPOs is 0.1407 (Table 3, Panel B, Column 3), while in the industry regressions, the sensitivity of Δ*Analyst* within an industry to industry IPOs is 0.4155 (Table 4, Panel B, Column 3). It is likely this difference in results in related to industry heterogeneity that is not considered in the market-level analyses (Garrett (2003)).

We also find that some of the forces that affect analyst presence at the industry level are distinct from those at the market level. In untabulated analysis, we re-examine the industry regression, but also include controls for market-level determinants. For example, in addition to including *Number of IPOs* at the industry level in our model, we also control for *Number of IPOs* in the market. *Number of IPOs* and Δ*Trading Volume* (at the industry level) remain positively and significantly associated with changes in the number of analysts at the industry level, and their effects are not subsumed by controlling for market *Number of IPOs* and market Δ*Trading Volume*. Interestingly, the coefficient on market-level *Returns* is positive and significant, while industry-level *Returns* is positive but insignificant in this analysis, suggesting that overall stock market performance may be

[11] We re-estimate our industry regressions including lagged dependent variables as controls. For the levels models, our results are similar, except that *Number of Listed Firms* is no longer significant. The results from our changes models are unaffected by including this control.

a superior proxy for analyst revenue.

D. IPO Activity as a Determinant of Sell-Side Analyst Industry Scope

The previous analyses indicate that IPO activity strongly relates to changes in the number of analysts as a whole. However, the results presented in Figure 1d suggest that IPO activities may not affect all brokerage houses in the same way. In addition, one limitation of these analyses is that it can be particularly problematic to separately identify changes in analyst and IPO activity (i.e., reverse causality or correlated omitted variables). For example, the market and industry analyses do not eliminate the possibility that analyst-activity can potentially influence the number of IPOs in the market. To address these issues, we conduct two additional tests regarding changes in the number of analysts at the brokerage level. First, we examine whether sensitivity to IPO activity varies across different broker types. To the extent that IPOs proxy for profits that can be used to fund analyst services, we expect brokers that participate in IPOs and larger brokers to be more sensitive to variation in this measure. Our second approach uses the Global Settlement Act of 2003 as a quasi-natural experiment that restricts analysts' involvement in investment banking activities. The regulatory shock provides us with a unique setting for examining the causal effects of IPO activity on analyst services across different types of brokerage houses.

[Table V about here]

Table V, Panel A provides the results of regressions of changes in the number of analysts employed at a broker on the macro-level determinants discussed above in Section III.B. In Column 1, we first document similar results to those at the macro level for the full sample of broker houses. Both *Returns* and *Number of IPOs* are positive and significantly related to changes in the number of analysts ($p<.05$ and $p<.01$, respectively). In Columns 2 and 3, we cut the sample based on whether the broker has ever underwritten an IPO, using data obtained from SDC.[12] Consistent with our expectations, the coefficient on *Number of IPOs* for brokers who underwrite IPOs (0.0034) appears to be much larger than that for brokers who do not underwrite IPOs (0.0007). We obtain similar inferences when we cut the sample based on broker size (measured by the mean number of analysts employed by the broker over the sample period). Sensitivity to IPO activity is monotonically increasing with broker size, with the coefficient ranging from 0.0005 for small brokers (Column

[12]We thank Leonardo Madureira for sharing this data.

4) to 0.0107 for larger brokers (Column 6). In Panel B, we examine the statistical differences in coefficients across broker types by estimating the pairs of regression models with interactions for all independent variables with the various broker type indicators. We find that all of the differences for the coefficient on *Number of IPOs* are statistically significant. These results provide consistent evidence that brokers appear to react differently to IPOs, based on how relevant underwriting is to their profitability.

To address potential endogeneity issues, we exploit the variation in brokers sensitivity to IPO activity by using the Global Settlement Act (GS) as an exogenous shock. This further helps us identify the causal effect of IPOs on analyst activity. GS (and related sell-side research regulations) were initiated to curb the biased research produced by brokerage houses and resulted in 10 (and later, 12) of the largest, most prestigious banks paying nearly $1.4 billion in fines.[13] Among other provisions, GS created a "Chinese Wall" between the research divisions and the investment banking divisions of brokerage houses, effectively prohibiting analysts from aiding or influencing underwriting in any form. Importantly, this provision also prohibited the cross-subsidization of research activities from underwriting activities, drastically altering the compensation schemes among top analysts at investment banks. This regulatory shock changes the way broker firms profit from IPO activity and provides us with a natural laboratory to test how IPOs affect analyst following.

While the GS was officially enacted in April 2003, the likelihood of the regulations and their effects were anticipated much earlier. For example, during the summer of 2001, Congress held the "Analyzing the Analysts" hearings, which led self-regulatory organizations, NASD and NYSE to enact new rules in July 2002 (NYSE Rule 472 and NASD Rule 2711); see for example, Kadan et al. (2009). We also searched news wires around this period and found several reports indicating that many major brokerage houses were anticipating the implementation of the regulation associated with GS. For example, Craig and Smith (2002) warned that brokers could be expected to reduce their research budgets by more than 20% in the coming year, partly in due to the pending analyst regulations. To be conservative, we consider the regulation period to begin in September 2001 when the shape of the regulations seem to have been anticipated by the market (using September 2002

[13]The ten original investment banks include Bear Stearns; Credit Suisse First Boston; Goldman Sachs; Lehman Brothers; J.P. Morgan; Merrill Lynch, Pierce, Fenner & Smith; Morgan Stanley; Citigroup Global Markets; UBS Warburg; and U.S. Bancorp Piper Jaffray. In August 2004, Deutsche Bank and Thomas Weisel were added to the settlement.

as the focal point does not affect the results reported below).

To examine these effects, we use a difference-in-difference (DD) design where the dependent variable is monthly changes in the number of broker-level analysts using three year windows around September 2001. Formally, we estimate the following model:

$$\begin{aligned}\Delta Analyst_{b,t} = \alpha_0 + \alpha_1 Post \times Treated_{b,t} + \alpha_2 Post_t + \alpha_3 Treated_b + \alpha_4 Merge_t \\ + \gamma \cdot MktDet_t + \sum_m \zeta_m + \epsilon_{b,t}.\end{aligned} \tag{4}$$

Post is an indicator variable that takes the value of 0 for the 36 months prior to September 2001 and a value of 1 for the 36 months after September 2001. We require that all brokers in the analysis employ at least 10 analysts over the period and exist on I/B/E/S for at least 1 full year prior to and after the regulation date; however, our results are robust to this decision. *Treated* is an indicator variable that takes the value of 1 if the broker is in the treated group and 0, otherwise. We detail the alternative treatment groups below. *Merge* is an indicator variable that takes the value of 1 if the broker merges with another broker in the month, 0 otherwise. We control for months in which a broker acquires another brokers because they are likely to directly increase the number of analysts. *MktDet* is a vector of control variables that include the determinants variables from Equation 3, above. The coefficient on *Post*× *Treated* (α_1) indicates the incremental change in monthly analyst changes between the pre and post periods for treated versus untreated brokers.

Our Treated Sample consists of sanctioned brokers and brokers who underwrite high numbers of IPOs. Following regulation, these brokers can no longer fund the research division of the bank using underwriting fees, and their ability to fund analyst services from IPO activity is severely limited. More specifically, we use three alternative sets of treatment and control groups based on brokerage house characteristics. The first treatment group consists of the 12 sanctioned brokers, where all other brokerage houses are considered part of the control group.[14] The second treatment group comprises firms who have above the median level of IPO issues between 1999 and 2004. These firms are most likely to be affected by the Chinese Walls and the inability to compensate research analysts by their contribution to the investment banking divisions. The third treatment group comprises brokerage houses that have any IPO activity between 1999 and 2004.[15] In each

[14] Recently, several brokers stopped reporting to I/B/E/S (e.g., Merrill Lynch and Lehman Brothers). For this portion of the analysis, we use a 2006 vintage of the I/B/E/S data.

[15] IPO data is collected from Bloomberg and manually matched to brokers using the most recent BRAN (Broker

case we expect the treated brokers, whose profits are highly sensitive to GS-related sanctions, to reduce analysts more than their peers (i.e., non-treatment brokers) following the regulation (i.e., $\alpha_1 < 0$).

[Table VI about here]

Table VI provides the results from the DD analysis. In Column 1, we examine the results when the treatment group is Sanctioned Brokers. In Column 2, we provide the results for when the treatment group is High IPO Issuers (i.e., above the median). Column 3 provides the results when the treatment group is any IPO Issuer. The coefficients of each of the alternative treated types (*Sanctioned*, *High IPO Issuer*, and *IPO Issuer*) interacted with the post regulation period is negative and significant. Following regulation, sanctioned brokers lose, on average, about 1 more analyst per month than the non-sanctioned brokers. We obtain similar results for the two IPO treatment groups. High IPO Issuers lose 0.791 analysts more per month than low IPO Issuers; and IPO issuers lose 0.722 analysts more per month than non IPO issuers. These results are highly significant at the 1% level.

The DD analysis in Table VI controls for many potential biases caused by unobserved variables that are common to both the treated and control brokers and is robust to various window lengths and other reasonable event dates. In untabulated analyses, we re-examine our results and include controls for $Post \times MktVars$, allowing for sanctioned brokers to have different sensitivities to market proxies following the regulation. Our results are robust to inclusion of these variables, thus reducing the possibility that these findings are driven by changes in market conditions following the 2001 crisis as opposed to regulations.

Additionally, our results are robust to a number of other alternative explanations. To rule out the possibility that our results are solely a function of the fees paid by sanctioned banks, we continue to find that IPO issuers lose more analysts per month than non IPO issuers after excluding sanctioned brokers from our analysis. Also, when we examine a placebo test around the Recession of 1991, we find no differential effects between broker types after the event, suggesting that our results are not simply driven by a financial market downturn. Our results also continue to hold if we exclude all technology analysts, providing evidence that this phenomenon is not solely driven by the technology bubble. Further, our inferences are similar when we examine change in firms

Translation file) available. I/B/E/S no longer produces this table, so we use a version from 2007.

covered as another dimension of scope. Treated firms reduce coverage by 5-8 more firms per month than non-treated brokers following the regulations.

Taken together, the results from the brokerage-level analysis suggest IPO activity affects analyst presence and coverage differently across brokerage houses. Analyst presence is more sensitive to IPO activity at investment banks that underwrite IPOs. These results are consistent with the decreasing number of analysts at larger broker houses relative to small brokerages as depicted in Figure 1d. Brokerage houses whose profits were more sensitive to the regulatory change experience a larger reduction in sell-side research leading us to suggest that profits, and IPO profits in general, are one determinant of the scope of the sell-side research industry.

IV. Consequences of Changes in Industry Analyst Following

A. Background and Motivation

Thus far we have provided evidence consistent with market conditions, particularly market performance and IPOs, influencing changes in the scope of analyst activities. However, this analysis raises the question of whether these changes have any real economic impact? Do changes in the scope of the sell-side analyst industry affect the quality and informativeness of analyst reports? Do they affect the way prices impound information?

We address these issues by examining how changes in the number of analysts covering an industry ($\Delta Analyst_{i,t}$) affect two key features of the aggregate information environment: 1) aggregate earnings forecast properties (accuracy and bias) and 2) the informativeness of public disclosure (market response to analyst reports and earnings announcements). We focus exclusively on the industry level for these analyses as it provides a reasonable setting by which analysts aggregate themselves and is also the level where we expect interactions between analysts to be most important. For example, we do not expect that changing the number of analysts in the Retailing sector is likely to have a strong systematic impact on the behavior of analysts in less related sectors. In addition, as previously explained, the industry-level poses fewer econometric issues than the market-level setting.[16] Further, we focus only on changes in the number of analysts in this section

[16] As mentioned above, the market level analysis requires a time-series methodology that suffers from well-known econometric problems (e.g., serially correlated residuals, non-stationarity, etc.). The broker level is also limited in that we are unable to aggregate the independent variables by broker.

as it is more amenable to the quasi-natural experiments we employ in our tests.

Aggregate earnings forecast properties are a natural starting point for examining economic consequences of changes in the sell side equity analyst industry. Analysts reports are one of the most important products they generate, and earnings forecasts are the most frequently changing feature of these reports. High quality forecasts are important to institutions, can lead to prestigious awards (e.g., II Ranking/WSJ Survey) and have been shown to increase analysts chances of promotion (Hong and Kubik (2003)). Indeed, many brokerage houses now subscribe to services such as Starmine which allow them to track their teams performance via quantitative analysis of analysts forecasts. Hence, earnings forecasts are an important performance metric that we can use to evaluate the quality of analyst reports.

A priori, it is not clear how changes in the number of analysts affect the quality of earnings forecasts in terms of their aggregate accuracy and bias. On the one hand, as analysts are often evaluated relative to their peers (Mikhail, Walther, and Willis (1999)) and compete with each other for prestigious rankings, adding more analysts may lead to less biased forecasts at the industry level (similar to the firm-level results of Hong and Kacperczyk (2010)) and potentially more accurate forecasts. On the other hand, new entering analysts are often less experienced and provide less accurate forecasts and recommendations than their seasoned peers (Hong et al. (2000a)). They also tend to issue overly optimistic earnings forecasts in hope of career promotion (Hong and Kubik (2003)). Thus, more analysts could result in an information environment with less accurate and more optimistically biased forecasts in the aggregate.

We can also evaluate the benefits of having more analysts by examining the aggregate informativeness of their reports to market participants. Importantly, analyst reports and companies' earnings announcements represent two potentially competing sources of information. First, as more analysts enter the fray, the overall amount of information production and processing increases, and there is a greater *quantity* of information available to market participants. This increased information can lead to relatively less reliance on the actual earnings announcements, as analysts play an information discovery role in the period leading up to the announcements (Chen, Cheng, and Lo (2010)). In other words, having more analysts increases the chances that information from earnings announcements is already impounded in prices prior to the earnings announcement. Second, as analysts often adopt a top-down industry perspective and estimate industry fundamentals (Hui and

Yeung (2013)), adding more analysts can also increase the *quality* of industry-level information. Recent examples illustrate how individual analysts can identify important industry information. In October 2007, Meredith Whitney downgraded much of the banking stocks she followed after predicting that problems in banks bond exposure would hurt their bottom lines. Similarly, the steel stock rally came to a roaring halt in January 2013 after a Goldman Sachs analyst predicted shortages of copper in China. Thus, when more analysts enter an industry, there are more opportunities for industry-level news to affect information flows.

Similarly, it is also important to note that our industry perspective allows us to examine information flows that may not be firm-specific, thus capturing different effects than those studied at the firm level (e.g., Piotroski and Roulstone (2004); Chan and Hameed (2006); Crawford, Roulstone, and So (2012)). Increased analyst presence within an industry can indirectly improve the flow of information for a firm, even if the firm does not receive added coverage. More analyst coverage within an industry may have a spillover effect that results in intra-industry information transfers (e.g., Hilary and Shen (2013)). For example, consider a tech analyst covering Samsung. If an additional tech analyst enters the industry and covers Apple, but not Samsung, the information in the analyst reports for Apple may help Samsung's investors to understand the competition and better anticipate Samsung's earnings announcement news. Our tests focus on these types of industry effects which are more difficult to examine in firm level tests.

B. *Data and Methodology*

We measure changes in the number of analysts based on two different approaches. Our first approach employs a quasi-natural experiment involving brokerage house closures and mergers to measure changes in the number of analysts at the industry level. This approach has been recently examined at the firm-level in various finance studies to improve the internal validity of tests that examine the impact of changes in analyst following (e.g., Kelly and Ljungqvist (2007); Hong and Kacperczyk (2010); Derrien and Kecskés (2013)). We extend prior work by applying this approach at the industry level and extending it to measures of aggregate forecast accuracy and bias as well as to measures of price informativeness. A brokerage house closure/merger creates an exogenous drop in the number of analysts within an industry and thus provides us with clearer identification of the treatment effect of changes in the total number of analysts.

We use drops in analysts resulting from 52 brokerage houses disappearances between 1994 and 2008 that were examined in Derrien and Kecskés (2013).[17] 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 acquirer broker during the 12 months before the merger and for which only one analyst covers following the merger. While this experiment helps to mitigate endogeneity and internal validity issues, it does not speak directly to increases in aggregate analyst following in general and to an extent limits the scope of our empirical analysis.

To address concerns about the external validity and generalizability of our first approach, we also include all changes in the number of analysts at the industry level and include industry fixed effects to control for unobserved heterogeneity that is constant across industry groups over time. With this approach, we can examine the full sample of changes in total analysts ($\Delta Analyst$) and not restrict ourselves to any specific events. This approach, however, is still limited to the extent that we are unable to control for all possible time-varying omitted variables, which limits our ability to identify the direction of causality. Thus, our second approach is more general but has greater potential for endogeneity concerns, while the first more effectively isolates the effect of decreases in the number of analysts at the expense of being less general.

C. Results for Analyst Forecast Accuracy and Bias

As the first step of our investigation, we examine whether changes in the total number of analysts at the industry-level affect aggregate earnings forecast accuracy and bias. To construct our measures of accuracy and bias, we employ the following procedure. We first collect monthly consensus (mean) annual EPS forecasts for all firms in our sample. We exclude firm observations that experienced changes in analyst coverage during the preceding month to remove firm-level direct effects from our analyses. In other words, we aggregate our measures for firms where the number of analysts following them does not change, but allow for other analysts to enter or exit these firms'

[17]We thank the authors for sharing this data. For more details on how brokers are identified, please refer to their study.

industry. Each month, we compute signed forecast errors for each firm as the difference between the consensus EPS forecast minus the actual EPS, scaled by the absolute value of the consensus EPS forecast. As such, more positive forecast errors indicate higher optimistic bias. Similarly, we compute unsigned forecast errors for each firm by computing the absolute value of the difference between the monthly consensus EPS forecast less the actual EPS , scaled by the absolute value of the consensus EPS forecast. We average the unsigned (signed) forecast errors for each industry-month to create our measures of aggregate forecast errors. We do not scale by stock price as to avoid issues identified with market price scaling (Mian and Teo (2004)). Following Hribar and McInnis (2012), we exclude firms with absolute consensus forecasts less than 0.10 per share from our analysis to avoid issues with small scalars. Formally:

$$|FE|_{i,t} = \frac{1}{n}\sum_{j=1}^{n} \frac{|EPS_{j,t} - Consensus\ EPS_{j,t}|}{|Consensus\ EPS_{j,t}|}$$

$$FE_{i,t} = \frac{1}{n}\sum_{j=1}^{n} \frac{EPS_{j,t} - Consensus\ EPS_{j,t}}{|Consensus\ EPS_{j,t}|},$$

where t denotes month, j denotes firm, and i denotes industry. Intuitively, aggregate absolute forecast error (i.e., $|FE|_{it}$) is a proxy for accuracy in industry i in month t and aggregate forecast error (i.e., FE_{it}) is a proxy for bias in industry i in month t. We further emphasize that j includes *only* firms that did not experience a change in analyst following during the prior month.

To examine the effects of changes in analysts on earnings forecast accuracy and bias, we estimate the following regression:

$$Fchar_{i,t} = \alpha_1 \Delta Analyst_{i,t-1} + \boldsymbol{\gamma} \cdot IndDet_{i,t} + \sum_i Industry_i + \sum_m \zeta_m + \epsilon_{i,t} \tag{5}$$

where $Fchar_{i,t}$ is one of two forecast characteristics: aggregate forecast accuracy ($|FE|$) or aggregate forecast bias (FE). $IndDet$ contains industry determinants of analyst activity (i.e., $Returns$, $\Delta Trading\ Volume$, $\Delta Volatility$, $\Delta Broker\ Profits$, $\Delta Economic\ Activity$, $Number\ of\ IPOs$, and $Net\ Delistings$) explored in Section III above. We include industry fixed-effects to account for differences in the quality of aggregate analyst forecasts across industries. We also include a vector of calendar month fixed effects (i.e., January, February, 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.[18] We lag $\Delta Analyst$ by one month to correct for potential endogeneity in the current period estimates of $FChar$. Standard errors are clustered by industry and month.[19]

If there are benefits associated with increasing the number of analysts, we expect to see improved accuracy and reduced optimistic bias associated with increases in the number of analysts. When $FChar = |FE|$, $\alpha_1 < 0$ implies that increases in the total number of analysts providing forecasts in an industry in the current month improve the accuracy in the next month (i.e., reduces aggregate error). When $FChar = FE$, $\alpha_1 < 0$ implies that increases in the number of analysts reduce optimistic bias in the next month.

[Table VII about here]

Table VII provides the results for forecast accuracy. We begin by measuring changes in analysts ($\Delta Analyst_{i,t-1}$) using brokerage house mergers and closures as a quasi-natural experiment to identify exogenous changes in analysts. As explained previously, this approach provides better internal validity and more cleanly identifies the effect of changes in the number of analysts in an industry. The results based on this approach are provided in Column 1. The coefficient on $\Delta Analyst_{t-1}^{BrokerMC}$ suggests that a one unit drop in the number of analysts in an industry decreases the average earnings forecast accuracy by 2.8% (statistically significant at the p=0.01 level).

While these results are economically and statistically significant, this approach employs only drops in analysts and cannot be extended to all changes in the number of analysts. To address whether our results hold in a more general setting, we further examine the relation between accuracy and all changes in analysts. Column 2 provides the results based on this approach. The coefficient $\Delta Analyst_{t-1}^{All}$ is negative and significant (p<0.05) and suggests that a one unit change in the number of analyst is related to a 0.5% changes in average forecast accuracy.

We further compare the differences in the economic magnitudes of the effects of the different measures of changes in analysts by including aspects of both measures in a single regression. Specifically, we decompose $\Delta Analyst_{t-1}^{All}$ into $\Delta Analyst_{t-1}^{BrokerMC}$, the drop in analyst coverage resulting from any brokerage house merger or closures in a month and $\Delta Analyst_{t-1}^{Other}$, the remaining change

[18] The majority of firms in each industry have fiscal periods that end with calendar quarter ends (i.e., March , June, September, and December).

[19] To preserve the full sample, we do not include institutional holdings as a control variable in the consequences analysis. However, all of the results in this section are robust to controlling for institutional holdings.

in the number of analysts. The results of this analysis are provided in Column 3. While the coefficients on both measures are negative and significant ($p < 0.01$), we find that the effect related to $\Delta Analyst_{t-1}^{BrokerMC}$ is more than seven times greater than that of $\Delta Analyst_{t-1}^{Other}$ based on an F-test of the coefficients ($p = 0.02$). This is consistent with $\Delta Analyst_{t-1}^{BrokerMC}$ providing a cleaner measure of changes in analysts.

[Table VIII about here]

Table VIII provides the results for a similar analysis based on average forecast bias (i.e,. signed forecast errors) rather than accuracy (i.e., unsigned forecast errors). As before, we first examine the effect of changes in the number of analysts on average forecast bias using changes in analyst related to brokerage house mergers and closers to more cleanly identify the effect of changes in analysts. The results of this analysis are provided in Column 1. The coefficient on $\Delta Analyst_{t-1}^{BrokerMC}$ suggests that a one unit drop in the number of analysts in an industry results in a 2.6% increase in optimistic forecast bias (significant at the $p = 0.05$ level).

In addition, we consider more general changes in the number of analysts in Column 2. The coefficient on $\Delta Analyst_{t-1}^{All}$ suggests that a one unit increase in the number of analyst relates to 0.5% decrease in average forecast bias ($p < 0.01$). As before, we further compare the economic magnitude of the effects in Columns 1 and 2, by breaking down all changes in analysts based on whether they relate to brokerage house mergers or closers. The results in Column 3 indicate that the effects of changes in analysts related to broker mergers are more than six times higher than other changes (based on an F-test, $p = 0.04$).

While these results cannot be directly compared to Hong and Kacperczyk (2010) since their study is performed at the firm-level, the implications are similar. Models based on general changes in analysts tend to underestimate the effects of changes in industry analysts on aggregate accuracy and bias. Overall, the results from both measures of changes in the number of analysts provide a consistent message that increases in total number of analysts improve the overall quality of their reports. In addition, since we exclude firm-level direct effects from our analysis, our results suggest that changes in the number of analysts at the industry-level have effects on the properties of analyst forecasts that extend beyond those documented in firm-level studies. We further explore this result by considering whether our results relate to new analysts providing relatively better forecasts than existing analysts. In untabulated results, we find no evidence of significant differences between the accuracy or the extent of optimistic bias of new entrants compared to existing analysts. These results suggest that the impact of new analysts is more complex and related to new analysts having a positive effect on the existing analyst pool.

D. Results for the Informativeness of Public Disclosure

We next examine the effect that changes in the number of industry analysts have on the sensitivity of prices to public disclosures. To examine this issue, we create two measures to proxy for the informativeness of public disclosure. The first measure of public disclosure informativeness is a proxy for the average informativeness of analyst forecasts. Similar to 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 analyst informativeness (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.[20] We exclude days within a 3-day window around earnings announcement and those corresponding to management earnings forecast dates available in the First Call CIG database.[21] Then, for each industry-month, we average all firm analyst informativeness ratios across all firms in an industry that did not experiences a change in analyst following. Formally:

$$AnalystINFO_{i,t} = \frac{1}{n}\sum_{j=1}^{n} AI_{j,t}$$

$$AI_{i,t} = \frac{\sum\limits_{d=1}^{NREVS} |Ret_{j,d} - DecRet_{j,d}|}{\sum\limits_{d=1}^{20} |Ret_{j,d} - DecRet_{j,d}|},$$

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. *Ret* is the daily return obtained from the CRSP Daily Stock File and *DecRet* is the size decile adjusted return obtained from the CRSP Portfolio file.

[20] We reexamined our analyses by scaling the dependent variable, *AnalystInfo*, by the number of analysts in an industry or including a control for the number of analysts in an industry. Our inferences remain unchanged in terms of economic sign and significance when we implement either of these approaches.

[21] The results of our analysis remain unchanged when we exclude dates with multiple analyst reports as in Loh and Stulz (2011).

The second measure is an aggregate measure of firm information content around earnings announcement dates. We construct a measure that is similar in spirit to the one employed by Francis, Schipper, and Vincent (2002), which proxies for the "usefulness of earnings announcements." We first collect all quarterly Earnings Announcement Dates from I/B/E/S that fall within 5 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 3-day window around the earnings announcement.[22] For each industry-month, we then average all of the $ACARs$ for firms within the industry that did not experience a change in analyst following. Formally:

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

$$ACAR_{j,t} = \sum_{d=-1}^{1} |Ret_{j,d} - DecRet_{j,d}|$$

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

To examine how changes in the number of analysts relate to these measures of the price informativeness of analyst reports and earnings announcements. We estimate the following model:

$$InfoType_{i,t} = \alpha_1 \Delta Analyst_{i,t-1} + \gamma \cdot IndDet_{i,t} + \sum_i Industry_i + \sum_m \zeta_m + \epsilon_{i,t} \tag{6}$$

Where $InfoType$ is one of two informativeness measures: $AnalystINFO$ or $EAINFO$. $IndDet$ contains the same set of control variables as in Equation 5, except we now also control for the magnitude of information content in a given month (i.e., $|Returns|$). We examine the same measures of changes in the number of analysts used in the previous results. Higher numbers of analysts should increase the informativeness of the analyst reports while potentially decreasing the informativeness of earnings announcements. If this is truly the case, we expect $\alpha_1 > 0$ when $InfoType = AnalystINFO$ and $\alpha_1 < 0$ when $InfoType = EAINFO$.

[Table IX about here]

[22] The results of our analysis remain unchanged when we exclude 3-day windows around earnings guidance dates and dates with multiple analyst reports.

Table IX provides the results from these tests.[23] In Panel A we examine the effect of changes in the number of analysts on the informativeness of analyst reports. Consistent with our expectations, we find in Column 1 that decreases in analysts related to brokerage house mergers and closures reduce the average informativeness of analyst reports increases by about 0.23% ($p < 0.05$). We also find in Column 2 that more general changes in the number of analysts are also related to the informativeness of analyst reports. However, these results appear to be driven mostly by changes in analysts related to brokerage house mergers and brokers. As noted in the column 3, when we examine these results together, we find that the coefficient on $\Delta Analyst_{t-1}^{BrokerMC}$ is more than 11 times higher than that of $\Delta Analyst_{t-1}^{Other}$ (based on an F-test, p= 0.001) and the coefficient on $\Delta Analyst_{t-1}^{Other}$ is not statistically significant. The difference in these results is likely to relate to the notion that these other changes are more endogenous and less cleanly estimate the effect of changes in analysts.

In Panel B, we examine the effect of changes in analysts on the average informativeness of earnings announcements. We first find in Column 1 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 0.22% ($p < 0.01$). We also find that the direction and significance of this effects persists when we consider more general changes in analysts following (Column 2). Similar to prior results, we again find that the estimated effect on the changes related to broker house mergers and closures is significantly higher than other changes (F-test, p=.013).

Taken together the results in Table IX suggest that increasing the number of analysts providing coverage within an industry can improve the overall flow of information, thereby disseminating important value-relevant information to investors earlier than the earnings announcement date. These findings are also consistent with firm-level evidence suggesting that analysts serve an "information discovery" role in the period leading up to the earnings announcement (Chen et al. (2010)) and suggest that this process is also a function of the extent of overall analyst presence in an industry. Further, to the extent that the information 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.

[23] Sample sizes vary slightly since some industry-months have no earnings announcements (e.g., Banking (GICS 4010)).

V. Conclusion

Analysts are often regarded as key actors in financial markets due to their ability to disseminate and distribute essential financial information. They also provide important services to the banks they are affiliated with by promoting stocks related to underwriting and brokerage business and facilitating access to management for clients (e.g., institutional investors). However, little is known about the factors that help shape the scope of the sell-side analyst industry as a whole and whether changes in this industry have aggregate economic consequences. In this study, we provide the first examination of the economic factors affecting changes in the scope of the sell-side analyst industry and also test whether these changes affect the quality of analyst reports and price formation.

We first document that measures of economic and financial market growth and profitability within the financial services industry are positively related to the number of analysts in the market. Across the market and industry levels, our results show that analyst activity is strongly associated with aggregate returns and IPO activity. Our results are largely consistent using alternative measures of analyst presence, including changes in the number of brokers and changes in the number of firms covered by analysts. These findings complement firm-level studies on the determinants of analyst coverage (e.g., Bhushan (1989); Chen and Ritter (2000); Barth et al. (2001), Jegadeesh et al. (2004)), and add a new dimension to our understanding of analyst activities. More broadly, our determinants analysis also sheds light on the factors related to entry in the financial services industry and contributes to a number of studies examining entry across other industries (e.g., Ellis et al. (2002); Barrot (2013))

We also conduct additional analyses to explore the effect of investment banking activities on the total number of analysts. We find that the relation between changes in the number of analysts and aggregate IPO activities differs by brokerage house type. Our evidence suggests that analyst employment at larger brokerages and those that underwrite IPOs is more sensitive to aggregate IPO activity. We further explore this result through a difference-in-difference analysis using the Global Settlement Act as a quasi-natural experiment that cuts the ties between investment banking fees and analysts compensation among brokers with IPO activities. Our findings suggest that brokers that participate in IPO activities reduced the number of analysts employed by twelve more analysts per year, on average, than other brokers in the three years following the regulation. Further, relative to other brokerage firms, investment banks not only reduced the number of analysts they employed but also significantly reduced the number of firms they cover. These results further strengthen our findings that changes in the number of aggregate analysts depend on factors related to investment banking activities.

The latter portion of our study focuses on the economic impact associated with changes in the number of analysts. Prior research examines how changes in the number of analysts affect the accuracy and bias of analyst forecasts for individual firms. The questions we ask here are distinct from the individual-firm studies. First, we examine whether changes in the number of aggregate analysts have an effect on the aggregate quality of analysts reports as well as industry price formation. Second, we concentrate on spill-over effects by calculating our aggregate variables after removing individual firm observations that experience direct changes in analyst coverage. In other words, we aggregate our measures for firms where the number of analysts following them does not change, allowing for other analysts to enter or exit these firms' industry. To address potential endogeneity issues, we conduct our analyses using both fixed effects regressions as well as a natural experiment involving brokerage house closures and mergers. Our results show that when there are more analysts in an industry, forecast accuracy improves, forecast optimism decreases, and the information in analyst reports is impounded into prices faster, over and above any direct effects of changes in analysts at the firm level.

Overall, the findings of this study broadly suggest that the analyst industry has been expanding over time, and that this expansion has positive externalities for market participants. Our results suggest that, in addition to the direct effects, increased analyst presence affects firms indirectly, through spill-over effects that increase the efficiency of information flows across an industry. These issues are relevant not only to the corporations and brokerage houses that employ analysts, but also to the investors that rely on analyst research as well as the regulatory bodies that oversee this industry.

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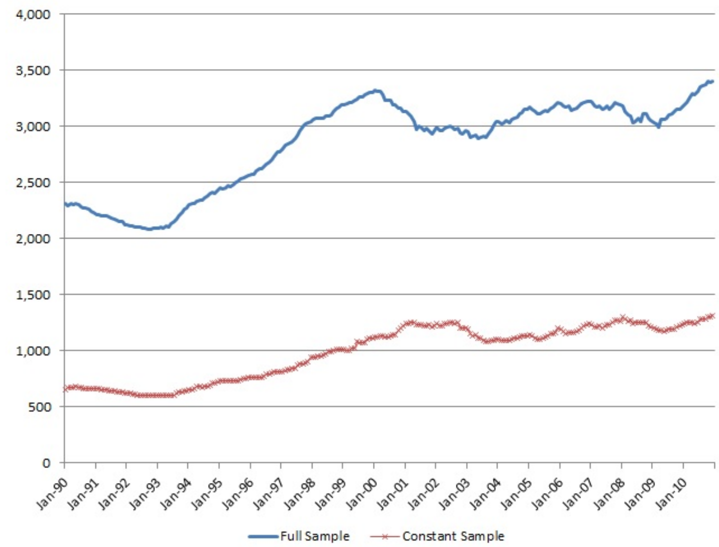
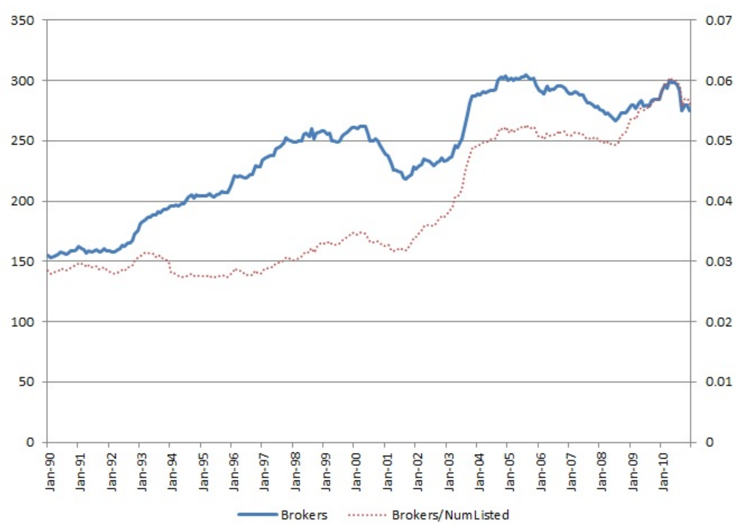
Figure 1. Time Series Plot of Analyst Activity (1990-2010)

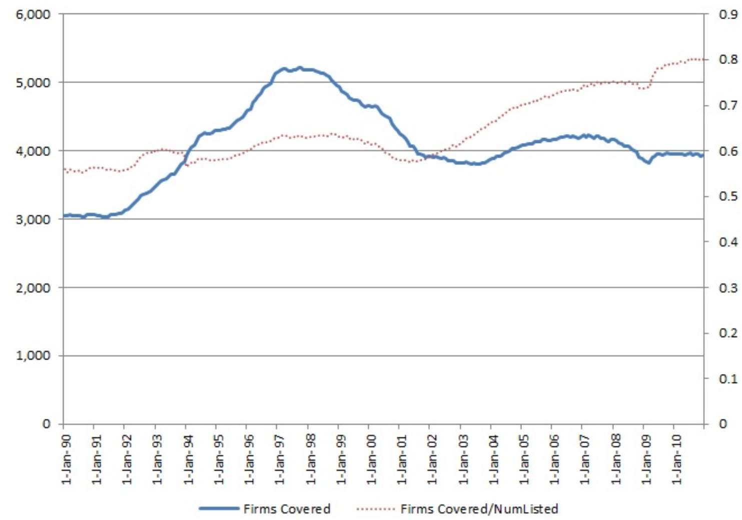
(a) Number of Analysts



(b) Number of Brokers



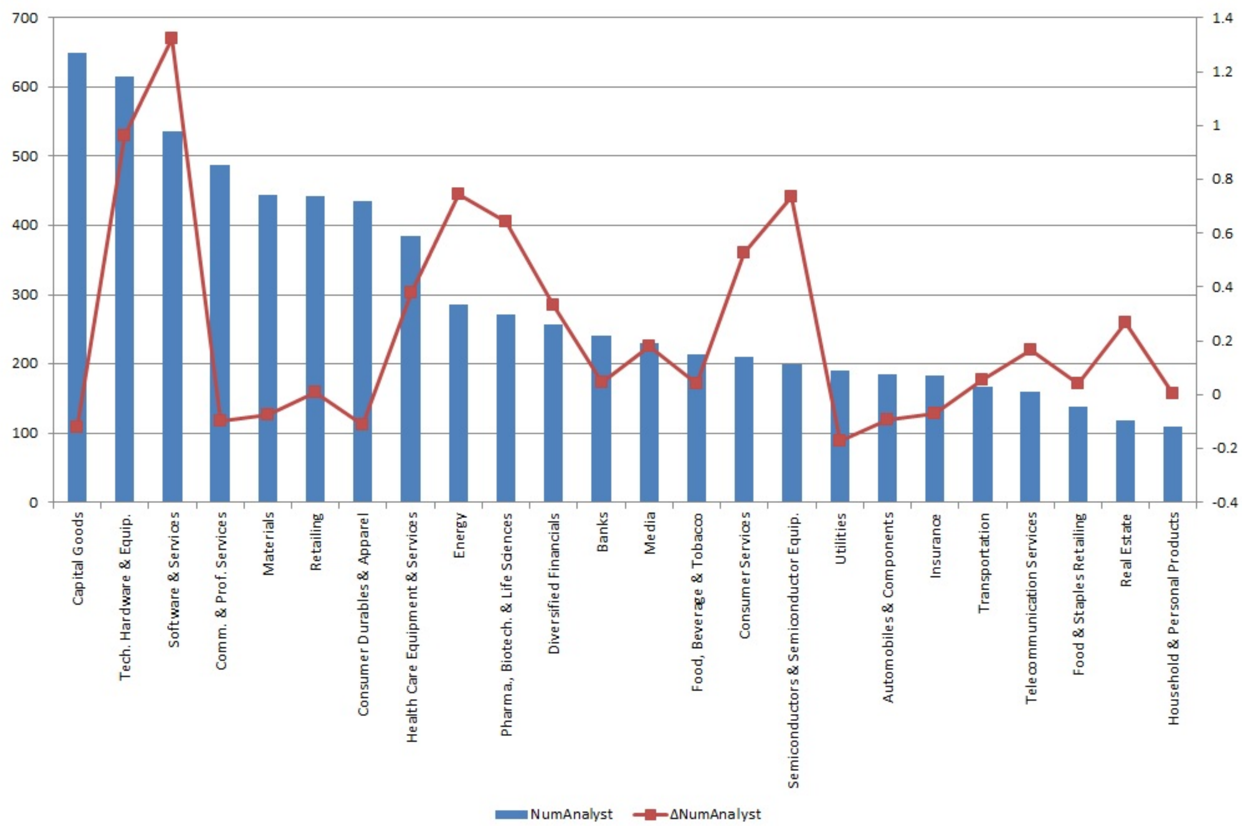
(c) Number of Firms Covered



(d) Number of Analysts by Broker Size Group

This figure provides time series plots of analyst activity as reported on I/B/E/S each month between 1990 and 2010. Panel A presents the plot of the number of analysts. The blue line represents the full sample and the red line is for a constant sample of brokers with reports every month throughout the period. Panel B presents the plot of number of I/B/E/S brokers. The blue line (and left axis) represent the number of brokers and the red dotted line (and right axis) represent the number of brokers scaled by the number of listed firms, as reported by CRSP. Panel C presents the plot of number of firms covered by I/B/E/S. The blue line (and left axis) represent the number of firms and the red dotted line (and right axis) represent the number of firms scaled by the number of listed firms, as reported by CRSP. Panel D presents the plot for subsets of brokers based on size. Small brokers have, on average, less than ten analysts over the sample period; medium brokers have, on average, 10-30 analysts over the sample period; large brokers have, on average, more than 30 analysts over the sample period.

Figure 2. Number of Analysts by Industry (1990-2010)



This figure displays the average number of analysts and average monthly changes in analysts from 1990-2010 across 24 GICS Industry Groups.

Table I: Examining Analyst Scope

This table describes the market and broker samples. Panel A contains the market sample and is comprised of 252 monthly observations from 1990-2010. $\Delta Analysts$ is the difference between the number of new analysts and the number of exiting analysts in a month. We define a new analyst as an analyst issuing her first forecast in the sample, or who has not issued a forecast in the past 12 months. An exiting analyst is defined as an analyst issuing her last forecast in the sample, or who does not issue a forecast in the next 12 months. $Analysts$ is the number of analysts from the prior period plus $\Delta Analysts$. $\Delta Brokers$ and $Brokers$ are the differences and levels of the monthly estimator codes on I/B/E/S, respectively. $\Delta FirmsCovered$ is the difference between the number of new firms receiving coverage and the number of exiting firms losing coverage in a month. We define a new firm as a firm receiving coverage for the first time in the sample, or who has not received coverage in the past 12 months. An exiting firm is defined as a firm receiving its last coverage in a given month, or who does not receive coverage in the next 12 months. $FirmsCovered$ is the number of firms from the prior period plus $\Delta FirmsCovered$. We use the number of unique analysts (firms) providing (receiving) forecasts in 1989 as a base year for computing the running total of analysts and firms. Panel B contains the broker sample of Number of Analysts. IPO activity is determined by whether the broker is ever associated with underwriting activity in the sample period (from SDC). We assign broker sizes based on the mean number of analysts covering a broker over the sample period. Small brokers have an average of less than 10 analysts over the sample period; medium brokers have 10-30 analysts; large brokers have more than 30 analysts.

Panel A: Market Sample

Variable	Mean	Median
$\Delta Analyst$	4.52	5.50
$Analysts$	2,847.52	3020.00
$\Delta Brokers$	0.48	0.00
$Brokers$	239.71	249.00
$\Delta FirmsCovered$	3.54	4.00
$FirmsCovered$	4,104.85	4071.00

Panel B: Broker Sample

	Brokers	*Analysts*
By IPO Activity:		
Non-IPO Brokers	605	3.67
IPO Brokers	211	18.23
By Size Group:		
Small (Mean <10 analysts)	696	3.21
Medium (Mean 10-30 analysts)	86	16.85
Large (Mean >30 analysts)	34	56.39

Table II: Descriptive Statistics

This table describes the descriptive statistics for determinants variables used in the market and industry analysis. *Market Cap* is the sum of all firms market cap in the market (industry). *Returns* are calculated by computing the value-weighted market (industry) portfolio returns each month, using a firms prior month market-cap weight in the market (industry). *Number of Listed Firms* is the number of firms (from CRSP) in the market (industry). *Number of IPOs* is the number of completed offerings in the market (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* is the difference between monthly IPOs and the change in listed firms. *Trading Volume* is the sum of all firms' trading volume (in number of shares) in the market (industry) over the past month. *Volatility* is the standard deviation of the market (industry) value-weighted daily returns over the month. *Broker Income* is the sum of quarterly net income for all firms in GICS Group 4020 (Diversified Financials), spread evenly across each month within the quarter. *Economic Activity* (CFNAI) is the Chicago Fed National Activity Index, obtained from the Federal Reserve Bank of Chicago. *Institutional Holdings* is the dollar value of aggregate market (industry) value owned by institutional investors based on 13-f filings

Variable	Mean	STD	Q1	Median	Q3
Market Determinants					
Market Cap ($Billions)	11,500.370	5,439.259	5,435.258	12,457.338	15,822.995
Returns	0.008	0.046	-0.020	0.014	0.039
Number of Listed Firms	6,409.210	1,037.258	5,575.000	5,899.000	7,472.000
ΔNumber of Listed Firms	-2.163	46.651	-23.000	-6.500	15.000
Number of IPOS	24.353	21.874	7.000	16.000	39.000
Number of Delistings	26.516	43.694	11.500	26.500	39.000
Trading Volume (Billions)	159.445	105.814	82.971	150.396	195.623
ΔTrading Volume (Billions)	0.245	89.050	-21.073	0.646	22.173
Volatility	0.010	0.006	0.006	0.009	0.011
ΔVolatility	-0.000	0.004	-0.002	-0.000	0.002
Broker Income ($Millions)	3,164.936	4,823.720	1,095.564	2,616.599	4,756.439
ΔBroker Income ($Millions)	86.889	4,739.179	-330.880	104.522	564.789
CFNAI	-0.175	0.874	-0.535	-0.030	0.420
ΔCFNAI	0.001	0.666	-0.435	0.000	0.405
Institutional Holdings ($Billions)	6,754.612	3,422.131	3,409.209	7,161.926	9,207.266
ΔInstitutional Holdings ($Billions)	42.079	380.961	-93.128	62.830	250.661
Industry Determinants					
Market Cap ($Billions)	491.546	431.947	183.722	352.866	673.342
Returns	0.009	0.059	-0.022	0.012	0.043
Number of Listed Firms	273.806	180.166	146.000	215.000	374.000
ΔNumber of Listed Firms	-0.085	6.214	-2.000	0.000	1.000
Number of IPOS	1.044	2.387	0.000	0.000	1.000
Number of Delistings	1.129	6.185	0.000	1.000	3.000
Trading Volume (Millions)	6.769	22.887	0.862	2.281	4.950
ΔTrading Volume (Millions)	0.011	17.667	-0.285	0.008	0.328
Volatility	0.012	0.008	0.007	0.010	0.014
ΔVolatility	-0.000	0.005	-0.002	-0.000	0.002
Institutional Holdings ($Billions)	288.424	250.624	105.397	208.431	395.960
ΔInstitutional Holdings ($Billions)	1.750	29.152	-4.364	1.723	9.496

Table III: Market-level determinants of Analyst Scope

This table provides the results from regressions of the number of analysts and other scope variables at the market level. Panel A provides OLS regressions of the level of analysts ($Analyst_{t+1}$) on market proxies for analyst-related profit sources. Panel B provides OLS regressions of changes of analysts ($\Delta Analyst_{t+1}$). Panel C contains other scope variables defined as follows: In Column 1, $\Delta Analyst$ is the change of number of analysts (defined in Table 1). In Columns 2-4, $\Delta Analyst$ is scaled by market cap ($MCAP$), number of listed firms ($NumListFirms$), and the number of firms with continued coverage over the past month ($NumCovFirm$), respectively. In Column 5, $\Delta Brokers$ is the change in the number of brokers on I/B/E/S. In Column 6, $\Delta FirmsCov$ is the aggregate change in the total number of firms covered. A new (exiting) firm is measured if it has no coverage in the 12 months prior to (following) the month of observation. In Column 7, $\Delta FirmsCov$ is scaled by the number of listed firms ($NumListFirms$). Market proxies for analyst-related profit are defined in Table II. All regression results are based on Newey-West adjusted standard errors. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

Panel A: Levels Regressions

	(1)	(2)	(3)
Market Value	**0.0613*** **	**0.0612*** **	**0.0718*** **
	(16.41)	**(16.28)**	**(2.65)**
Number of Listed Firms	**0.0732*** **	**0.0687*** **	**0.0668** **
	(3.97)	**(3.42)**	**(2.25)**
Trading Volume	0.0718	0.0737	0.0839
	(0.58)	(0.60)	(0.70)
Volatility	**13,672.7090*** **	**14,646.5173*** **	**14,687.1904*** **
	(5.34)	**(5.60)**	**(5.81)**
Broker Profits	**0.0104*** **	**0.0098*** **	**0.0100** **
	(2.81)	**(2.61)**	**(2.57)**
CFNAI		15.6766	15.1769
		(0.79)	(0.68)
Inst. Holding			-0.0147
			(-0.34)
Constant	**1,537.9379*** **	**1,562.5540*** **	**1,541.5357*** **
	(11.09)	**(10.58)**	**(7.88)**
Month FE?	Yes	Yes	Yes
Observations	252	252	237
R-squared	0.90	0.90	0.89

Panel B: Changes Regressions

	(1)	(2)	(3)	(4)
Returns	**125.7719*** **	**123.2567*** **	**124.8356*** **	**168.2096*** **
	(3.89)	**(3.83)**	**(3.87)**	**(3.10)**
ΔNumber of Listed Firms	**0.0888*** **			
	(3.16)			
Number of IPOs		**0.1429** **	**0.1407** **	**0.1085* **
		(2.17)	**(2.16)**	**(1.71)**
Number of Delistings		**-0.0752** **	**-0.0754** **	**-0.0809** **
		(-2.50)	**(-2.54)**	**(-2.57)**
ΔTrading Volume	0.0000	0.0000	0.0000	0.0000
	(0.87)	(0.84)	(0.82)	(0.46)
ΔVolatility	350.3458	344.7934	349.5336	349.4468
	(1.12)	(1.10)	(1.10)	(1.07)
ΔBroker Profits	**0.0007*** **	**0.0007*** **	**0.0007*** **	**0.0007*** **
	(4.47)	**(4.31)**	**(4.09)**	**(4.37)**
ΔCFNAI			1.4751	1.8302
			(0.97)	(1.19)
ΔInst. Holding				-0.0045
				(-0.81)
Constant	13.7373	6.6591	6.5485	6.3255
	(0.34)	(0.16)	(0.16)	(0.15)
Month FE?	Yes	Yes	Yes	Yes
Observations	252	252	252	236
R-squared	0.32	0.32	0.33	0.36

Panel C: Other Scope Measures

VARIABLES	(1) $\Delta Analyst$	(2) $\frac{\Delta Analyst}{MCAP}$	(3) $\frac{\Delta Analyst}{NumListFirms}$	(4) $\frac{\Delta Analyst}{NumCovFirm}$	(5) $\Delta Brokers$	(6) $\Delta FirmCov$	(7) $\frac{\Delta FirmCov}{NumListFirms}$
Returns	**124.8356*** **	**0.0000*** **	**0.0210*** **	**0.0627*** **	**15.8719*** **	71.3882	**0.0210*** **
	(3.87)	**(2.98)**	**(3.79)**	**(3.89)**	**(3.34)**	(1.54)	**(3.79)**
Number of IPOs	**0.1407** **	**0.0000*** **	0.0000	0.0000	0.0092	**0.5134*** **	0.0000
	(2.16)	**(3.46)**	(1.37)	(1.35)	(0.93)	**(4.38)**	(1.37)
Number of Delistings	**-0.0754** **	**-0.0000** **	**-0.0000*** **	**-0.0000** **	-0.0017	**-0.3031*** **	**-0.0000*** **
	(-2.54)	**(-2.55)**	**(-2.71)**	**(-2.55)**	(-0.43)	**(-3.74)**	**(-2.71)**
ΔTrading Volume	0.0000	0.0000	0.0000	0.0000	-0.0000	-0.0000	0.0000
	(0.82)	(1.36)	(0.79)	(1.11)	(-0.28)	(-0.02)	(0.79)
ΔVolatility	349.5336	0.0000	0.0685	0.1864	24.0525	-13.4443	0.0685
	(1.10)	(0.71)	(1.30)	(1.20)	(0.51)	(-0.03)	(1.30)
ΔBroker Profits	**0.0007*** **	**0.0000** **	**0.0000*** **	**0.0000*** **	-0.0000	**0.0008*** **	**0.0000*** **
	(4.09)	**(2.48)**	**(4.07)**	**(3.80)**	(-0.30)	**(2.94)**	**(4.07)**
ΔCFNAI	1.4751	0.0000	0.0002	0.0008	0.0573	0.9956	0.0002
	(0.97)	(0.87)	(0.79)	(1.04)	(0.20)	(0.50)	(0.79)
Constant	3.8752	-0.0000	0.0007	0.0024	0.1919	7.5269*	0.0007
	(1.00)	(-0.10)	(1.09)	(1.17)	(0.25)	(1.65)	(1.09)
Month FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252	252	252
R-squared	0.33	0.25	0.32	0.32	0.10	0.44	0.32

Table IV: Industry-level determinants of Analyst Scope

This table provides the results from regressions of the monthly number of analysts at the industry level across 24 GICS Industry Groups from 1990-2010. Panel A provides OLS regressions of the level of industry analysts ($Analyst_{i,t+1}$) on industry proxies for analyst-related profit sources. Panel B provides OLS regressions of changes of industry analysts ($\Delta Analyst_{i,t+1}$). Industry proxies for analyst-related profit are defined in Table II. Standard errors are double clustered by industry and month. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

Panel A: Levels Regressions

	(1)	(2)	(3)
Market Value	**0.0488*** **	**0.0488*** **	-0.0304
	(3.81)	**(3.86)**	(-1.01)
Number of Listed Firms	**0.3575*** **	**0.3573*** **	**0.4026*** **
	(3.78)	**(3.57)**	**(4.08)**
Trading Volume	**0.1846* **	**0.1846* **	**0.1490* **
	(1.91)	**(1.90)**	**(1.75)**
Volatility	114.2565	119.1153	298.2137
	(0.42)	(0.45)	(1.15)
Broker Profits	-0.0001	-0.0001	-0.0002
	(-0.23)	(-0.21)	(-0.54)
CFNAI		0.1046	2.6439
		(0.04)	(1.07)
Inst. Holdings			**0.1396** **
			(2.38)
Month FE?	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes
Observations	5,877	5,877	5,532
R-squared	0.96	0.96	0.96

Panel B: Changes Regressions

	(1)	(2)	(3)	(4)
Returns	**5.9610****	**5.5234****	**5.5330****	**4.5040****
	(2.56)	**(2.54)**	**(2.55)**	**(2.02)**
ΔNumber of Listed Firms	0.0868			
	(1.28)			
Number of IPOs		**0.4157*****	**0.4155*****	**0.4142*****
		(6.45)	**(6.46)**	**(6.41)**
Number of Delistings		-0.0581	-0.0581	-0.0574
		(-1.32)	(-1.33)	(-1.32)
ΔTrading Volume	**0.0093*****	**0.0079*****	**0.0079*****	**0.0075*****
	(9.07)	**(6.08)**	**(6.11)**	**(5.90)**
ΔVolatility	-14.6309	-14.4962	-14.5208	-8.3236
	(-0.71)	(-0.69)	(-0.69)	(-0.40)
ΔBroker Profits	**0.0001****	**0.0001****	**0.0001****	**0.0001****
	(2.21)	**(2.14)**	**(2.09)**	**(2.26)**
ΔCFNAI			0.0267	0.0317
			(0.17)	(0.21)
ΔInst. Holdings				0.0048
				(1.52)
Month FE?	Yes	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes	Yes
Observations	5,877	5,877	5,877	5,509
R-squared	0.09	0.11	0.11	0.12

Table V: Broker Level Sensitivity to Market-wide factors

This table provides the results from regressions of the number of analysts at the broker level. The results are based on OLS regressions of changes of broker analysts ($\Delta Analyst_{b,t+1}$) on market proxies for analyst-related profits, as defined in Table II. The sample consists of monthly observations from 1990-2010 for 816 Brokers. Panel A presents the results from panel regressions of $\Delta Analyst_{b,t+1}$ using various broker samples. Column 1 presents the results for the full sample. Columns 2 and 3 present the results for subsamples based on whether the broker ever has IPO activity during the sample. Columns 4-6 present the results for different subsets of brokers based on size. Small brokers have an average of less than 10 analysts over the sample period; medium brokers have 10-30 analysts; large brokers have more than 30 analysts. Panel B contains the differences in coefficient estimates for number of IPOs from a fully interacted regression across different broker types. The rows indicate the broker type and the corresponding column in Panel A. Standard errors are double clustered by broker and month. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

Panel A: Changes Regressions

	Full Sample	*Underwrites IPOs?*		*Size*		
		No	Yes	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Returns	**0.5762*** **	**0.3054** **	**0.8652*** **	0.1060	**0.7284** **	**4.3051*** **
	(3.45)	(2.00)	**(2.71)**	(1.23)	**(2.24)**	**(3.27)**
Number of IPOs	**0.0022*** **	**0.0005* **	**0.0030*** **	**0.0005** **	**0.0016** **	**0.0107*** **
	(4.73)	**(1.67)**	**(4.66)**	**(2.10)**	**(2.03)**	**(6.15)**
Number of Delistings	**-0.0006*** **	**-0.0003*** **	**-0.0007*** **	**-0.0002** **	**-0.0007*** **	**-0.0022** **
	(-2.94)	**(-2.97)**	**(-2.69)**	**(-2.05)**	**(-3.23)**	**(-2.38)**
ΔTrading Volume	0.0000	0.0000	0.0000	0.0000	0.0001	-0.0000
	(0.61)	(1.23)	(0.34)	(0.77)	(0.69)	(-0.09)
ΔVolatility	0.2569	**2.4486* **	-1.5076	1.0255	-2.1000	3.1137
	(0.19)	**(1.81)**	(-0.53)	(1.30)	(-0.50)	(0.24)
ΔBroker Profits	0.0000	-0.0000	0.0000	**0.0000* **	**-0.0000* **	0.0000
	(1.49)	(-0.37)	(1.45)	**(1.95)**	**(-1.69)**	(1.49)
ΔCFNAI	0.0028	0.0057	-0.0004	0.0030	-0.0107	0.0337
	(0.38)	(1.02)	(-0.03)	(0.57)	(-0.63)	(0.72)
Broker FE?	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,856	27,863	30,993	39,731	13,589	5,536
Number of Brokers	816	605	211	696	86	34

Panel B: Differences in Number of IPOs' Coefficients Across Broker Types

IPO (3) - No IPO (2)	**0.0027*** **
	(3.57)
Medium (5) - Small (4)	**.0015***
	(1.79)
Large (6) - Medium (5)	**.01028*** **
	(4.86)
Large (6) - Small (4)	**.0118*** **
	(5.85)

Table VI: The Effects of Analyst-Regulation on IPO-Sensitivity

This table provides difference-in-differences regression results of $\Delta Analyst_{b,t}$ across brokers that were more and less likely to be affected by sell-side analyst industry regulations:

$$\Delta Analyst_{b,t} = \alpha_0 + \alpha_1 Post \times Treated_{b,t} + \alpha_2 Post_t + \alpha_3 Treated_b + \alpha_4 Merge_t + \gamma \cdot MktDet_t + \sum_m \zeta_m + \epsilon_{b,t}.$$

$Post$ is an indicator variable that takes the value of 0 for the 36 months prior to September 2001 and a value of 1 for the 36 months after September 2001. $Treated$ is an indicator variable that takes the value of 1 for if the broker is in one of three treatment groups (defined below) or 0, otherwise. $Merge$ is an indicator variable that takes the value of 1 if the broker merges with another broker in the period, or 0 otherwise. $MktDet$ includes market determinants from Table II. The three alternative treatment groups include (1) Sanctioned Brokers; (2) High IPO Issuers; and (3) IPO Issuers. Sanctioned Brokers include the 12 Sanctioned GS Brokers. High IPO Issuers include all firms with IPO issues above the median value between 1999 and 2004. IPO Issuers include any firm that issues an IPO between 1999 and 2004. Standard errors are clustered by broker and month. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

Variable	(1)	(2)	(3)
Sanction × Post Regulation	**-1.097***** **(-3.92)**		
High IPO Issuer × Post Regulation		**-0.791***** **(-3.35)**	
IPO Issuer × Post Regulation			**-0.722***** **(-3.39)**
Sanctioned	**0.594***** **(3.76)**		
High IPO Issuer		**0.323**** **(2.21)**	
IPO Issuer			**0.432**** **(2.36)**
Post Regulation	0.131 (0.85)	0.171 (1.23)	**0.360**** **(2.07)**
Returns	-1.607 (-1.43)	-1.595 (-1.42)	-1.587 (-1.41)
Number of IPOs	**0.006**** **(1.98)**	**0.006**** **(1.98)**	**0.006**** **(1.98)**
Number of Delistings	0.002 (0.62)	0.002 (0.61)	0.001 (0.61)
ΔTrading Volume	-0.000 (-1.02)	-0.000 (-1.02)	-0.000 (-1.02)
ΔVolatility	-8.338 (-0.47)	-8.343 (-0.47)	-8.343 (-0.47)
ΔBroker Profits	0.000 (0.91)	0.000 (0.91)	0.000 (0.91)
ΔCFNAI	-0.098 (-0.94)	-0.098 (-0.94)	-0.098 (-0.95)
Merger Month?	**6.132***** **(7.03)**	**6.198***** **(6.09)**	**6.270***** **(6.16)**
Month FE?	Yes	Yes	Yes
Observations	2,575	2,575	2,575
R-squared	0.07	0.07	0.06

Table VII: The Effect of Analyst Following on Forecast Accuracy

This table provides panel regressions of aggregate industry forecast accuracy on changes in aggregate analyst following at the industry level. Our proxy for accuracy is the industry absolute forecast error ($|FE|$) and is constructed as follows. We first compute unsigned forecast errors for each firm as the absolute value of the difference between actual EPS and the monthly 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 direct effects from our analyses. We average the forecast errors for each industry-month to create measures of aggregate forecast accuracy. Changes in aggregate analyst following are measured as follows: $\Delta Analyst^{All}_{t-1}$ is defined as in Table I. $\Delta Analyst^{BrokerMC}_{i,t-1}$ is the number of analyst drops resulting from brokerage houses mergers or closures. An analyst is considered to have dropped if she provides reports for the closed/merged broker house in the 12 months prior to the event date and provides no reports for any brokerage house in the 12 months after the event date. $\Delta Analyst^{Other}_{i,t-1}$ is the difference between $\Delta Analyst^{All}_{i,t-1}$ and $\Delta Analyst^{BrokerMC}_{i,t-1}$. Other control variables include $Returns$, $\Delta Trading\ Volume$, $\Delta Volatility$, $\Delta Broker\ Profits$, $\Delta CFNAI$, $Number\ of\ IPOs$, and $Net\ Delistings$, as defined in Table I above. Standard Errors are clustered by industry and month. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

VARIABLES	(1)	(2)	(3)
$\Delta Analyst^{BrokerMC}_{t-1}$	**-0.0278*** **		**-0.0290*** **
	(-2.57)		**(-2.66)**
$\Delta Analyst^{All}_{t-1}$		**-0.0050*** **	
		(-3.28)	
$\Delta Analyst^{Other}_{t-1}$			**-0.0039*** **
			(-3.03)
Other Controls?	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes
Observations	5,854	5,854	5,854
R-squared	0.13	0.13	0.13

Table VIII: The Effect of Analyst Following on Forecast Bias

This table provides panel regressions of aggregate industry forecast bias on changes in aggregate analyst following at the industry level. Our proxy for bias is the signed industry forecast error (FE) and is constructed as follows. We first compute signed forecast errors for each firm as the absolute value of the difference between the monthly EPS forecast and actual EPS 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 direct effects from our analyses. We average the forecast errors for each industry-month to create measures of aggregate forecast bias, where more positive forecast errors indicate higher levels of optimistic bias. Changes in aggregate analyst following are measured as follows: $\Delta Analyst_{t-1}^{All}$ is defined as in Table I. $\Delta Analyst_{i,t-1}^{BrokerMC}$ is the number of analyst drops resulting from brokerage houses mergers or closures. An analyst is considered to have dropped if she provides reports for the closed/merged broker house in the 12 months prior to the event date and provides no reports for any brokerage house in the 12 months after the event date. $\Delta Analyst_{i,t-1}^{Other}$ is the difference between $\Delta Analyst_{i,t-1}^{All}$ and $\Delta Analyst_{i,t-1}^{BrokerMC}$. Other control variables include $Returns$, $\Delta Trading\ Volume$, $\Delta Volatility$, $\Delta Broker\ Profits$, $\Delta CFNAI$, $Number\ of\ IPOs$, and $Net\ Delistings$, as defined in Table I above. Standard Errors are clustered by industry and month. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

VARIABLES	(1)	(2)	(3)
$\Delta Analyst_{t-1}^{BrokerMC}$	**-0.0258****		**-0.0271****
	(-2.30)		**(-2.41)**
$\Delta Analyst_{t-1}^{All}$		**-0.0052*****	
		(-3.35)	
$\Delta Analyst_{t-1}^{Other}$			**-0.0043*****
			(-3.10)
Other Controls?	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes
Observations	5,854	5,854	5,854
R-squared	0.10	0.10	0.10

Table IX: The Effect of Analyst Following on Public Disclosure Informativeness

This table provides panel regressions of aggregate industry informativeness measures on changes in aggregate analyst following at the industry level. Panel A presents the results for $AnalystINFO$ and Panel B presents the results for $EAINFO$. $AnalystINFO$ is calculated by averaging firm-level Analyst Informativeness (AI) across all firms within an industry-month, where AI is the ratio of absolute-size adjusted 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 3-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. Changes in aggregate analyst following are measured as follows: $\Delta Analyst^{All}_{t-1}$ is defined as in Table I. $\Delta Analyst^{BrokerMC}_{i,t-1}$ is the number of analyst drops resulting from brokerage houses mergers or closures. An analyst is considered to have dropped if she provides reports for the closed/merged broker house in the 12 months prior to the event date and provides no reports for any brokerage house in the 12 months after the event date. $\Delta Analyst^{Other}_{i,t-1}$ is the difference between $\Delta Analyst^{All}_{i,t-1}$ and $\Delta Analyst^{BrokerMC}_{i,t-1}$. Other control variables include $|Returns|$, $Returns$, $\Delta Trading\ Volume$, $\Delta Volatility$, $\Delta Broker\ Profits$, $\Delta CFNAI$, $Number\ of\ IPOs$, and $Net\ Delistings$, as defined in Table I above. Standard Errors are clustered by industry and month. ***,**, and * denote 1%, 5% and 10% level of significance respectively.

Panel A: Analyst Informativeness

VARIABLES	(1)	(2)	(3)
$\Delta Analyst^{BrokerMC}_{i,t-1}$	**0.0023*** **		**0.0023*** **
	(3.56)		**(3.58)**
$\Delta Analyst^{All}_{t-1}$		**0.0002** **	
		(2.32)	
$\Delta Analyst^{Other}_{i,t-1}$			0.0002
			(1.43)
Controls?	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes
Observations	5,854	5,854	5,854
R-squared	0.33	0.32	0.33

Panel B: Earnings Announcement Informativeness

VARIABLES	(1)	(2)	(3)
$\Delta Analyst^{BrokerMC}_{i,t-1}$	**-0.0022*** **		**-0.0023*** **
	(-2.70)		**(-2.85)**
$\Delta Analyst^{All}_{t-1}$		**-0.0004*** **	
		(-2.62)	
$\Delta Analyst^{Other}_{i,t-1}$			**-0.0003** **
			(-2.14)
Controls?	Yes	Yes	Yes
Month FE?	Yes	Yes	Yes
Industry FE?	Yes	Yes	Yes
Observations	5,659	5,659	5,659
R-squared	0.31	0.30	0.31