Client Service, Compensation, and the Sell-Side Analyst Objective Function: An Empirical Analysis of Relational Incentives in the Investment-Research Industry

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This paper investigates how sell-side analysts build and sustain their client networks; the economic gains to successfully managing this challenge; and the metrics through which these incentives are delivered. In a typical semiannual period, the average analyst supplies around 80 research notes and three reports; spends around one week brokering meetings between client investors and corporate managers; and holds approximately 750 private phone calls and 45 one-on-one meetings with client investors. Changes in these client-service actions explain approximately fifty percent of the intertemporal variation in broker votes, a mechanism used to measure the value that client investors ascribe to maintaining continued analyst relations, with the strongest sensitivity observed for widely disseminated, thematic, research reports known as whitepapers. Analysts' client-service actions, however, explain relatively little intertemporal variation in commissions and broker share of trade execution in their covered stocks. Analysts who strengthen their client networks reap significant rewards and, consistent with the informativeness principle, we find these incentives to be delivered primarily through broker votes, not trades executed in analysts' covered stocks. Our findings contribute to understanding of the job and objective functions of sell-side analysts and structure of relational incentives in the investment-research industry.

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I. INTRODUCTION

Capital market participants indicate that the overriding objective of sell-side analysts is to build and protect their *franchise* (Groysberg 2010). The economics behind this assertion are relatively clear. An analyst with a strong franchise has a network of deep relationships with a broad set of important institutional clients who wish to retain access to repeat interaction with the analyst. This is important because of the loose linkage between sell-side service and buy-side payment. Given the difficulty in writing and enforcing complete contracts for information-based goods, analysts and their employers agree to bear the risk of uncompensated services in return for what they feel are higher payments from client investors (McNichols 1990). Theories of repeated games indicate that this risk is inversely related to the value that client investors ascribe to retaining access to repeat interaction with an analyst (Bull 1987; Levin 2003). Consequently, analysts' franchises are said to sustain the loose and often implicit contracts that govern the exchange of information and trading commissions in the investment-research industry (Eccles and Crane 1988).

While the importance of the franchise construct is relatively easy to discern, how it is managed and best operationalized are not. Accounting scholars have long wrestled with how to characterize the economic motives of sell-side analysts. Indeed, the lack of direct evidence on analysts' job and objective functions is believed to be a principal factor that "impedes our ability to further our understanding of sell-side analysts" (Bradshaw 2011, 39; see also, Lang 2008).

In this paper we contribute to scholarly understanding of these issues in two interrelated ways. First, we provide an empirical test of the primary measures said to represent the strength of an analyst's franchise. This test uses annual analyst-compensation data as a benchmark to evaluate how well each operationalization captures the information used to assess the strength of an analyst's franchise during compensation-award decisions. Because subjective assessments of analysts' franchises are the primary determinant of analyst-compensation-award decisions at most sell-side firms (Groysberg 2010; Groysberg and Healy 2013), these data provide an ideal setting to test the usefulness of each operationalization for understanding of analysts' economic motives. Second, we report the first direct and comprehensive evidence on the mix of services that define the client-facing side of the sell-side analyst job, and the relation between changes in the supply of these services and the dynamics of each operationalization of the franchise construct.

Two features of our research setting are noteworthy and distinguish our study from prior and concurrent work. The first is our proprietary panel dataset, collected and provided to us by a mid-to-large-sized investment bank.[1] These data provide rare access to analyst compensation and the three most commonly cited measures of an analyst's franchise, namely, the commissions from analysts' covered stocks, the bank's market share of trading volume in analysts' covered stocks, and analyst ratings known as "broker votes." They also provide direct and comprehensive measures of analysts' three modes of service delivery: *published research*—widely disseminated written communications with no personal contact or interaction; *concierge services*—scheduled communications that arise from the co-location of client investors and corporate managers; and *high-touch services*—private, personalized, and interactive

[1] Based on the Hong et al. (2000) categorization, the sample bank is classified as large/high status. Nevertheless, it is not part of the bulge bracket. As we discuss in Section 3, the bank is best viewed as approximating the employment environment of the median I/B/E/S analyst, although the bank itself is above the median in terms of size and status.

communications between analysts and client investors. This enables us to examine and control for the prevalence and implications of specific services, as opposed to noisy "catchall" proxies.[2]

The second distinguishing feature of our study is the unit of analysis. Extant work generally examines either the implications of sell-side analyst behavior for trading in *individual stocks* (Irvine 2004; Jackson 2005; Green et al. 2014a) or the value that *individual money managers* ascribe to analysts' various services (Bradshaw 2011; Brown et al. 2014). In contrast, we follow prior research on analysts' incentives (Mikhail et al. 1999; Hong and Kubik 2003; Groysberg et al. 2011) and aggregate actions and outcomes across each analyst's client network and coverage universe. That is, we perform our analyses at the analyst level.

Our use of analyst-level data is a natural choice given our research questions. First, they enable us to shed light on the mix of services that define the job of a typical *analyst*, as opposed prior research, which investigates the mix of published research and concierge services for a typical *firm* or *analyst-firm* pair (e.g., Soltes 2014; Green et al. 2014a). Second, they allow us to better capture the incentives and tradeoffs that sell-side analysts face in managing their franchise. For example, while anecdotal and survey evidence indicate that *individual clients* prefer time-intensive, personalized service, theory indicates that an analyst who provides such service will incur sizable opportunity costs in the form of other activities forgone (Holmström and Milgrom 1991). Consequently, an analyst who wishes to build and protect her *network* of client relations may prefer to use less personalized communication technology with greater economies of scale (e.g., widely disseminated published research). Moreover, many client services like whitepapers

[2] A vast literature uses forecasts and/or recommendations to proxy for analysts' published research or for client service more generally (see, for example, Frankel et al. 2006; Groysberg et al. 2011; Green et al. 2014a). As we show in Section V, these proxies have considerable measurement error. For example, we report that the average analyst supplies around eighty notes in each semiannual performance-evaluation period, but only thirty forecasts and two recommendation changes.

and high-touch meetings have multi-stock implications; and, prior research suggests that analysts' portfolios of covered stocks are purposely chosen to help them develop and maintain their franchises (Kini et al. 2009). The estimates obtained from investor- and analyst-firm-level data therefore should not be expected to yield valid inferences regarding the operationalization and dynamics of the franchise construct or sell-side analysts' relational incentives. In sum, analyst-level data are critical to addressing the questions that we are interested in.

Our results indicate that each franchise metric has a largely separate and markedly different association with the information contained in analyst-compensation awards. Notably, we find approximately 50% of the information in annual analyst-compensation decisions to be reflected in broker votes, around 13% in commissions from covered stocks, and 0% in broker share of trade execution in covered stocks. This general pattern is observed across a variety of different tests and specifications.

Given our finding that broker votes strongly and uniquely reflect the information used to assess analysts' franchises during annual compensation awards, a natural question is what factors explain the dynamics of broker-voting outcomes. Theory provides two non-mutually exclusive hypotheses. First, the value that client investors ascribe to maintaining continued analyst access may move with the ebbs and flows of market interest in an analyst's stocks for reasons outside of an analyst's control. In this case, our compensation results would simply reflect the bank's efforts to index analyst pay to market rates and would have no impact on analysts' on-the-job behavior (Oyer 2004). Second, the dynamics of analysts' franchises may reflect the actions that analysts take to serve client investors (Holmström 1979). In this case, our compensation results would suggest that franchise-management concerns shape analysts' on-the-job behavior.

We find statistical evidence consistent with both theories; but we find the latter to explain approximately 15 times more variation in broker-voting outcomes than the former. Indeed, we document that the dynamics of analysts' franchises, as reflected in cumulative broker-voting outcomes, can be predicted from changes in high-touch meetings and phone calls, as well as concierge services like non-deal road shows. Consequently, personal interactions and brokered meetings with corporate managers appear to be important inputs to the franchise-management process, even though these services generally incur high opportunity costs.[3] Our investigation also reveals that franchise-management concerns create an incentive to favor large clients and that analysts respond to this incentive. Specifically, we find that large clients, whose votes are ascribed greater weight during the franchise-evaluation process, receive a disproportionate share of private telephone calls, the most prevalent form of high-touch service.

Surprisingly, we find changes in the supply of widely disseminated, thematic research reports known as whitepapers to most strongly predict changes in the strength of analysts' franchises. A typical whitepaper yields a cumulative broker-voting response equivalent to approximately three field trips to corporate facilities, six non-deal road show days, forty high-touch meetings, or 140 client calls. These findings suggest that whitepapers, despite being non-timely and vulnerable to significant public-goods problems, are an important vehicle through which analysts signal their industry knowledge and build and sustain their franchise. This is important given that prior research has yet to document the mechanism through which analysts are rewarded for deep industry knowledge, although client-level survey data clearly substantiate that such knowledge is valued by institutional investors (Bradshaw 2011; Brown et al. 2014).

[3] Consistent with the hypothesis that time-consuming out-of-office interactions (e.g., non-deal road shows, conferences, and high-touch meetings) incur sizable opportunity costs, we find month-to-month changes in their provision to be negatively associated with changes in published research and a variety of other client services.

Our paper contributes to the sell-side analyst literature in two ways. First, we extend the growing literature on the role of relationships in the investment-research industry. Prior studies find evidence that analysts benefit from relationships with corporate managers and will incur costs to build and sustain these ties (Francis and Philbrick 1993; Brochet et al. 2014; Green et al. 2014a,b; Soltes 2014). Yet we know relatively little about how analysts cultivate and benefit from relationships with client investors (Gu et al. 2013). We present new evidence on how analysts build and protect their networks of client relationships, the economic gains to successfully managing this challenge, and the metrics through which these incentives are delivered.

Second, we shed light on the upper bound of the signal-to-noise ratio, and thus contracting value, of the measures most commonly said to approximate the analyst objective function. Prior literature routinely finds that analysts' client-service activities explain less than two percent of the variation in analyst ratings and broker share of trade execution in analysts' covered stocks (Irvine 2004; Jackson 2005; Emery and Li 2009; Green et al. 2011). For analyst ratings, our results indicate that these low signal-to-noise ratios are research-design artifacts. We find changes in a comprehensive and direct set of client-service variables to explain approximately fifty percent of the variation in broker votes; and, consistent with the informativeness principle (Holmström 1979; Banker and Datar 1989), we find broker votes to explain significant variation in analyst compensation awards. In contrast, our findings indicate that commissions from covered stocks and the broker share of trade execution in covered stocks are indeed largely uninformative about the actions that analysts take to serve client investors; and, consistent with the informativeness principle, we find these metrics to explain limited variation in analyst compensation awards. Our data thus indicate that the notion that sell-side analysts' are principally rewarded based on trade in their covered stocks is inconsistent with theories of optimal risk sharing in employment contracts and actual analyst-compensation-award decisions. Consequently, researchers should exercise caution when drawing inferences of analysts' incentives based on patterns in broker-share data (Irvine 2004; Jackson 2005; Juergens and Lindsey 2009).

The rest of the paper is organized as follows. In Section II, we provide an overview of related literature. Our research site and sample are described in Section III. Franchise-operationalization tests are reported in Section IV. In Section V we investigate the implications of client-service activity for the dynamics of analysts' franchises. Additional tests are reported in Section VI. Section VII concludes.

II. RELATED LITERATURE AND MOTIVATION

In this section we motivate our study by discussing related literature and placing our paper in the context of that literature.

The Relationship-Management Activities of Sell-Side Analysts

Prior research indicates that relationships are important to sell-side analysts. For example, when placed in a situation where a relationship with a corporate manager or important institutional client is potentially at risk, analysts appear willing to bias their forecasts and recommendations in order to maintain that relationship (Francis and Philbrick 1993; Gu et al. 2013).

Reflecting a growing awareness of the importance of relationships to the functioning of the investment-research industry, recent work has begun to investigate the actions that analysts take to build and sustain their relationships with *corporate managers* (e.g., Brochet et al. 2014; Green et al. 2014b; Soltes 2014). This work makes an important contribution to scholarly understanding of the information-gathering activities of sell-side analysts and the role of management relations in facilitating these activities.

Yet no matter how good an analyst is at gathering information and developing management contacts, she will not be rewarded unless she is able to develop and maintain relationships with important *institutional clients*. Ultimately it is institutional investors that fund sell-side research and act as the arbiters of analyst value (Ljungqvist et al. 2007).

Surveys of institutional investors provide some insight into analysts' client-relationship-management activities and incentives (Bradshaw 2011; Brown et al. 2014). Generally speaking, surveys indicate that buy-side money managers ascribe the greatest value to personalized analyst attention and brokered access to corporate managers. Ceteris paribus, it thus appears that the dominant strategy for a sell-side analyst who wishes to nurture a relationship with a particular client is to bestow high-touch and concierge services on that client.

Of course, sell-side analysts do not seek relationships with a single client: they strive to cultivate a network of clients, with an eye toward enhancing brokerage revenues. To draw valid inferences regarding analysts' economic motives, empiricists must therefore incorporate into their analyses the depth *and* breadth of analysts' client relationships, as well as whom those relationships are with, and how those relationships map into brokerage revenues. As we discuss below, extant work has been generally unable to do this due to data limitations. Yet such an analysis seems both important and necessary to further understanding of analysts' relational incentives. Indeed, when viewed through the lens of cultivating a *network* of clients who wish to retain continued analyst access, the relative benefits of less-personalized client-service technology—i.e., channels with greater economies of scale—seem more compelling. For example, a personalized, private meeting may create significant value for a *single* client; but a widely disseminated research note or report can create modest value for *dozens if not hundreds* of clients. Ultimately, how well changes in analysts' various client-service activities predict changes in the dynamics of their client *networks* remains an important and largely open empirical question.

The Franchise Construct: Theoretical and Institutional Underpinnings

Following convention within the investment-research industry, we use the term *franchise* as a descriptor that encapsulates the breadth, depth, and importance of an analyst's client ties (Groysberg 2010). In conceptual terms, an analyst with a strong franchise has a network of deep relationships with a broad set of important institutional money managers who wish to retain access to repeat interaction with the analyst.[4] An analyst can thus increase the strength of her

[4] We deliberately use the term *franchise* instead of *reputation* for two reasons. First, academic literature commonly uses the term reputation to mean seemingly similar but conceptually different things (Rindova et al. 2005; Pfarrer et al. 2010). Given that we have a very specific definition of reputation in mind—one that incorporates *whom* the reputation (or, more accurately, the *relationship*) is with—we have opted to employ the term and definition used by the economic agents whose incentives we seek to understand. Second, the sell-side analyst literature commonly equates the term reputation with an analyst's standing in ratings like those produced by *Institutional Investor (II)* magazine (e.g., Stickel 1992; Jackson 2005; Ertimur et al. 2009). Yet analyst ratings are just one indicator of the strength of an analyst's franchise—and one whose merits and meaning are hotly debated. Notably, Leone and Wu (2007) note that while *II* ratings are commonly used as a measure of reputation, "what exactly 'reputation' represents is still under debate three decades after the rankings were first introduced" (see also, Emery and Li 2009; Gresse and Porteau de la Morandière 2014).

franchise by cultivating: (1) *more* relationships with client investors; (2) *deeper* relationships with client investors; or (3) relationships *more important* (e.g., larger) client investors.

Theory and anecdotal evidence connect the franchise construct to brokerage revenues through a distinctive economic characteristic of the market interface between buy- and sell-side firms: the loose linkage between services supplied and trading-revenues received. Given the difficulty in writing and enforcing complete contracts for information-based goods, analysts and their employers agree to bear the risk of uncompensated services in return for what they feel are higher payments from client investors (Eccles and Crane 1988; McNichols 1990). This risk is inversely related to the value that client investors ascribe to maintaining ongoing analyst relationships (Bull 1987; Levin 2003). Consequently, analysts' franchises are said to sustain the loose and often implicit contracts that govern the exchange of information and trading commissions in the investment-research industry (Eccles and Crane 1988). Indeed, much like in professional sports, where franchise players are said to win games and generate revenue for their teams (e.g., Denlinger 1977; Wallace 1983), on Wall Street, analysts with strong franchises are said to "win" transactions and generate brokerage revenues for their firms (Groysberg 2010; Groysberg and Healy 2013).[5]

[5] The term *franchise player* has become institutionalized in the National Football League, where owners can designate one unrestricted free agent as a franchise player in each free-agent period. The franchise tag binds the player to the team and is used to retain valued contributors to organizational success (Weisman 1996).

Operationalizing and Investigating Analysts' Franchises: Prior Empirical Work

Prior work argues that analyst ratings and the commissions and broker share of trade execution in analysts' covered stocks can be used to draw inferences regarding the strength of analysts' franchises. Jackson (2005, 684) and Goldstein et al. (2009, 5195), for example, claim that because client investors are not contractually obligated to execute their trades through the recommending broker, prior evidence that they do indicates that transactions in analysts' covered stocks should be informative about the value that client investors ascribe to maintaining access to repeat interaction with an analyst. Similarly, the discussion in Stickel (1992) suggests that because analyst ratings like those compiled by *Institutional Investor* magazine aggregate the value that many institutional money managers ascribe to the sell-side analysts with whom they interact, analyst ratings should also be informative about the strength of analysts' networks of client ties.

Given these characterizations, the literatures on analyst ratings and trading commissions can be viewed as examining factors that shape the strength of analysts' franchises. Yet it is difficult to understand what these literatures tell us about analysts' client-service activities and incentives since they generally investigate: (1) analyst-firm-level, as opposed to analyst-level, data; (2) cross-sectional statics (levels), as opposed to intra-analyst dynamics (changes); and (3) only one, or at most, two client services at a time (e.g., Stickel 1992; Irvine 2004; Jackson 2005; Green et al. 2014a). These research-design choices imply that this work should not be expected to produce coefficient estimates that speak to the issues that we are interested in (Murphy 1985; Baker 1987).

Moreover, those few services that have been examined (i.e., forecasts, recommendations, and broker-hosted conferences) have been consistently shown to explain less than two percent of the variation in the chosen operationalization of the franchise construct (e.g., Jackson 2005, 689; Green et al. 2011, 44). These seemingly small signal-to-noise ratios suggest that either (1) the client services investigated by existing work do not capture the richness of the actions that analysts take to cultivate their networks of client relationships or (2) standard measures of the franchise construct do not contribute to more informative analyst evaluations, and thus will be largely ignored during franchise-evaluation and compensation-award decisions (Holmström 1979; Banker and Datar 1989). Either way, it appears that much remains to be learned about how sell-side analysts build and protect their network of client relations, the economic gains to successfully managing this challenge, and the metrics through which these incentives are delivered. The rest of this paper is devoted to investigating these issues.

III. RESEARCH SETTING AND DATA

Research Site

Our research site is one of the larger, mid-sized, full-service broker dealers.[6] During the 2004–2007 sample period, the bank typically employed around 30 analysts and maintained an active equity-trading desk. Each of the approximately dozen market makers who covered Nasdaq stocks and dozen traders who covered NYSE-listed stocks during the sample period traded roughly 50 stocks and generated volume in two ways: order-taking driven by research

[6] Firms within this category include Cowen, Evercore, FBR, Jefferies, JMP Securities, Lazard Capital Markets, Oppenheimer, Piper Jaffray, Raymond James, Robert W. Baird, Stifel, and William Blair. The research, sales, and trading operations of these firms are similar to those of the largest Canadian banks analyzed by Irvine (2001; 2004).

(i.e., institutional equity block trading) and market making. The bank also employed an institutional sales force that served as its primary contact with buy-side analysts and portfolio managers. Each of the approximately 30 sales force members employed during the sample period had a strong relationship with an average of 10 buy-side accounts.[7]

The sample bank provides a promising research setting for a number of reasons. First, it maintains rich information on client-service actions and outcomes, facilitating our tests. Second, it offers a clean, powerful research site: like other mid-sized banks, it derived the bulk of its order flow from its research offerings and did not engage in proprietary trading or use client commission arrangements (CCAs).[8] In contrast, bulge-bracket banks,[9] which have large research operations, attribute much of their transaction volume to their order-execution capabilities and algorithms (D'Antona 2011; Healy and Groysberg 2013). Finally, as we discuss below, the sample bank approximates the employment conditions faced by the median I/B/E/S analyst.

Data

Our primary analyses use three proprietary analyst-panel datasets. The first contains *monthly* information on commission revenues, trading volume, and a comprehensive set of client-service metrics for the years 2004–2007. We supplement these data with annual earnings

[7] Although most accounts were serviced by one salesperson, large accounts were often serviced by two (and, in rare cases, as many as four) institutional salespeople.

[8] Client commission arrangements (CCAs) enable the buy side to obtain research and execution from different sell-side firms. Under a CCA agreement, the investment manager trades with the broker that provides the best execution and instructs that broker to set aside a portion of the commission to pay the research provider. Like many mid-sized, U.S.-based banks during our sample period, the sample bank expected payment for its research to take the form of order flow (i.e., it did not accept payment through CCAs).

[9] Cowen et al. (2006, 140) define bulge banks as "the six largest and most reputed banks on Wall Street (Credit Suisse First Boston, Goldman Sachs, Merrill Lynch, Morgan Stanley Dean Witter, Salomon Smith Barney, and Lehman Bros)." Other common definitions during our 2004–2007 sample period include not only the six banks cited by Cowen et al., but also Bear Stearns, Deutsche Bank, and UBS.

forecasts from I/B/E/S[10] and firm-level trading volume[11] from CRSP and Datastream that we link to our analyst-month data file using a set of coverage/recommendation files supplied by the bank. All variables in this dataset are aligned contemporaneously in calendar time.

The second dataset contains *semiannual* broker votes for the five periods spanning January 1, 2004 to June 30, 2007. Each year, the bank collects votes over two windows. The first tallies votes from January to June, the second from July to December. The vote awarded by each client to a given analyst is then normalized to a 0–5 scale. Next, point allocations across all clients are weighted to generate an overall measure of the value of each analyst's research. Consistent with practice at many other banks, the sample bank weights votes using a system of tiers. Votes from first-, second-, and third-tier clients are weighted by factors of four, two, and one respectively.[12] Finally, each analyst's score is normalized by the maximum possible outcome, with the resulting amount expressed as a percentage. This process is summarized in Figure 1. We merge these data with the aforementioned monthly file using the approach recommended by the bank's research staff. Specifically, for each semiannual analyst observation in the voting file, we compute the total client-service activity for the six months beginning three months before the voting window. Thus, votes from the first (second) window are matched to client-service activity from October to March (April to September). Figure 2 provides a

[10] Consistent with the arguments and evidence in Groysberg et al. (2011), the sample bank did not track analyst forecasts.

[11] Firm-level trading volume indicates the volume of, say, Wal-Mart shares traded across all broker-dealers. Broker-firm-level trading volume, on the other hand, captures the volume of Wal-Mart shares traded through a given broker dealer, for example, Morgan Stanley or Goldman Sachs. Prior studies often examine brokers' market share of trading volume in analysts' covered stocks, which is computed by dividing broker-firm trading volume by firm-level trading volume (e.g., Irvine 2004; Niehaus and Zhang 2010).

[12] To confirm that votes are weighted based on client importance, we exploit annual commission and vote-weight data for each of the sample bank's clients (more than 800 institutions per year). As expected, we find a strong monotonic relation between commissions and voting tier, with mean (median) commissions ranging from $69,000 ($14,500) for non-voting clients to $7 million ($1.65 million) for top-tier (i.e., quadruple weighted) clients. Non-parametric tests performed by year and for the entire 2004–2006 sample indicate that inter-tier differences in commissions are statistically significant at the 1% level.

graphical representation of the voting and client-service windows for our second analyst-level dataset.

The third dataset contains *annual* analyst compensation for the years 2004–2006. We merge these data with our commissions and voting data using the approach employed by the sample bank. Specifically, for calendar year 2004, we average the January–June 2004 and July–December 2004 broker-vote outcomes by analyst. We then cumulate monthly commissions and trading data over the January–December 2004 period by analyst. We repeat this process for years 2005 and 2006. Finally, we merge the voting, commissions, and compensation data by analyst and year.

Our final monthly service-commission and semiannual service-voting datasets contain 1,414 analyst-month and 170 analyst-period observations, respectively. The former spans the entire range of the first data file—i.e., January 1, 2004 to December 31, 2007. The latter, because it requires client-service data for the three months preceding each voting window, begins six months later, on July 1, 2004, and ends on June 30, 2007, the close of the final vote window. Our annual compensation-commission-voting dataset contains 83 observations and spans the period January 1, 2004 to December 31, 2006.

In addition to the primary files discussed above, the bank supplied several supplemental spreadsheets that provide information on characteristics of the client-service and franchise metrics tracked in our main data files. These include a spreadsheet that provides detailed information on the bank's specialty client services during 2006 and a spreadsheet that tracks client-level telephone calling activity by analyst-month for the first three quarters of 2007. These data are discussed in greater detail in Sections V and VI.

Characteristics of the Sample Analysts

Table 1 provides descriptive information on the sample analysts. The average analyst is approximately 35–37 years old and has 5–6 years of experience recorded on the I/B/E/S detail file. Seventy percent of the analysts have an MBA, thirty-one percent have a CFA, and approximately 20 percent (ten percent) have been recognized by the *Wall Street Journal* or *Starmine* (*Institutional Investor*) at some point in their careers.[13] These statistics resemble the central tendencies of the broader I/B/E/S population, as documented in prior research (Clement 1999; De Franco and Zhou 2009; Brown et al. 2015); and they support our conjecture that the sample analysts experience employment conditions similar to those faced by the median I/B/E/S analyst.

IV. ANALYST-COMPENSATION TESTS

In this section we examine the relation between analyst compensation and each of the three franchise proxy variables. As noted earlier, prior field work indicates that subjective assessments of analysts' franchises are the primary determinant of analyst-compensation-award decisions at most sell-side firms. Compensation data thus provide a useful setting to test the informativeness of each operationalization of the franchise construct. These data also enable us to throw light on the economic rewards received (penalties incurred) by analysts who strengthen

[13] None of the analysts were *Institutional Investor (II)* rated during our sample period. Starmine, a division of Thomson-Reuters, in conjunction with the *Financial Times* produces annual rankings of analysts based on the accuracy of their forecasts and performance of their stock recommendations. The *Wall Street Journal (WSJ)* produces a similar rating based on analysts' stock picking performance. *II* magazine rates analysts based on a poll of institutional investors. Casual empiricism and the memoirs of former analysts (e.g., Reingold and Reingold 2006) indicate that *II* ratings are strongly influenced by the size of a bank's institutional sales force (see also, Emery and Li 2009). Analysts at mid-sized banks thus rarely place at the top of *II*'s poll. In contrast, the *Starmine* and *WSJ* awards are based on purely quantitative factors. Consequently, analysts from banks outside of the bulge are better represented in these awards (Emery and Li 2009).

(fail to sustain) their client networks as measured by each of the three franchise proxy variables. Finally, they enable us to address a key limitation of related work by Groysberg et al. (2011)—the only other study to investigate the determinants of analyst-compensation-award decisions.

Using data from a single high-status investment bank, Groysberg et al. (2011) present evidence that the outcomes of analyst-compensation-award decisions are associated with the outcomes of analyst ratings.[14] The economic reason for this association, however, remains unclear. For example, prior research argues that analyst ratings should matter for analyst-compensation only inasmuch as ratings are informative about trading in analysts' covered stocks (e.g., Jackson 2005, 685). A testable implication of this hypothesis is that the association between analyst ratings and analyst compensation should largely disappear when one controls for these commissions. Unfortunately, due to a lack of brokerage-level trading data, Groysberg et al. (2011) are unable to formally test this hypothesis. They instead leave it as an open question for future research (Groysberg et al. 2011, 995).

Our tests, which are reported in Table 2, yield the three key insights regarding the information used in analyst compensation-award decisions. First, they indicate that analyst ratings best reflect the information used to assess analysts' franchises during analyst-compensation-award decisions. This can be seen in the univariate results reported in Panels A through C, which show that the level of analyst compensation is strongly associated with aggregate votes awarded by client investors (Pearson correlation = 0.727, $p < 0.001$), moderately associated with commissions from analysts' covered stocks (Pearson correlation = 0.337, $p < 0.001$), and unrelated to the bank's share of trading volume in analysts' covered stocks (Pearson correlation = 0.024, $p = 0.830$). It can also be seen in the univariate results reported in the first

[14] For corroborating survey evidence, see Brown et al. (2015).

three columns of Panel D, which show that the same general pattern holds not only in levels, but also in first differences (i.e., changes).

Second, our results indicate that although analyst ratings do share some common information with our two transactions-based franchise metrics, they also reflect substantial unique information used in analyst-compensation-award decisions. For example, Panel D indicates that controlling for transactions in analysts' covered stocks only reduces the estimated effect of a 90th percentile change in broker votes (15.2%, unreported) from about seventeen percent of total compensation to about fourteen percent of total compensation (i.e., from about \$87,000 to about \$74,000 for a typical analyst).[15]

Finally, our results indicate that although commissions from analysts' covered stocks also contain some unique information incorporated in analyst-compensation-award decisions (albeit markedly less than that observed for broker votes),[16] the same cannot be said for the broker share of trade execution in analysts' covered stocks. Indeed, the results in Panels C and D indicate that the informational overlap between analyst compensation and the broker share of trade execution in analysts' covered stocks is too small to be considered economically meaningful. Consequently, researchers should avoid drawing inferences of analysts' incentives based on patterns in broker-share data (e.g., Irvine 2004; Jackson 2005; Juergens and Lindsey 2009; Niehaus and Zhang 2010).

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[15] The aforementioned percentage increases were computed as follows: $e^{0.885 \times 0.152} - 1 = 14.4\%$, $e^{1.039 \times 0.152} - 1 = 17.1\%$.

[16] For example, Panel D indicates that controlling for broker votes reduces the estimated effect of a 90th percentile change in the natural log of commissions from analysts' covered stocks (0.52, unreported) from about seven percent of total compensation to about five percent of total compensation (i.e., from about \$36,000 to about \$26,000 for a typical analyst).

V. CLIENT-SERVICE TESTS

Having established that broker votes best reflect the information used to evaluate analysts' franchises during compensation-award decisions, we now turn our attention to the client-facing side of the sell-side analyst job and its relation to the dynamics of analysts' franchises. We begin by reporting descriptive statistics for the typical mix of services that define the client-facing side of the sell-side analyst job. We then investigate the relation between changes in the frequency of these services and the dynamics of the three franchise proxy variables. By studying the relations between client-service activity and broker votes in a single, unified setting, we contribute to understanding of the marginal products of a wide range of client-service efforts (and thus the economic implications of analysts' efforts to build and sustain their franchises). By studying the service-franchise relation using not only broker votes, but also commissions from analysts' covered stocks and the broker share of trade execution in analysts' covered stocks we shed light on the signal-to-noise ratio of each of these franchise metrics (and thus why analyst ratings best explain the outcomes of the evaluation and remuneration decisions investigated in Section IV).

Descriptive Statistics: How do Analysts Serve Client Investors?

Analysts use three modes of service delivery to cultivate their franchises: published research, high-touch services, and concierge services.

Published Research. Analysts supply two kinds of written services that differ in content and form. Notes, the primary method used to disseminate timely, company-specific information (such as forecasts, recommendations, and price objectives), are short written commentaries.

Reports, lengthier and supplied less frequently, are more comprehensive communications generally written over several weeks or months. Because they are subjected to a lengthier editorial and publishing process than notes, the content of reports is typically less transaction oriented and more likely to emphasize deeper industry- and topic-specific concerns (Michaely and Womack 1999, 659). Thus, "if analysts have new information, notes, with their short production cycle, represent the more likely means to distribute this news" (De Franco and Hope 2011, 232).

As reported in Table 3, in a typical month the median analyst issued twelve new notes that contained five new forecasts. Only 22% of analyst months included at least one report. Whitepapers, the longest and most insightful types of reports, are particularly infrequent, occurring in only 3% of analyst-month observations (Panel A) and 13% of analyst-six-monthly observations (Panel B). Finally, Table 3 indicates that in 16% of analyst-month and 38% of analyst-six-monthly observations, an analyst "blasts" research to client investors through the bank's blast voicemail system.[17]

High-Touch Channels. Analysts supply two forms of high-touch service that differ in form and content, client meetings and telephone calls. To our knowledge, ours is the first study to throw light on these elusive client-service activities.

*Client Meetings***.** Private, face-to-face meetings between analysts and client investors are an important part of the sell-side analyst's job. They are generally scheduled well in advance and often involve significant travel time (sometimes to different cities or countries), making them poorly suited to communicating timely, transaction-oriented information. Consequently,

[17] Practitioners indicate that some analysts use blast voicemail systems to alert important clients to the release of significant, new research (Valentine 2011).

these meetings typically emphasize less urgent educational topics ranging from broad discussions of industry themes to interactive debates over information already reflected in security prices. Post-meeting synopses from 2006 (unreported) indicate that these meetings also provide an opportunity for clients to use the bank's analysts as a sounding board for their longer-term investment theses. Table 3 documents that this form of high-touch client service occurs regularly. For example, 71% of analyst-month observations include at least one such meeting, and in these months the median analyst holds eight meetings.

*Telephone Calls***.** Telephone conversations are a convenient channel for personalized client service well suited to transmitting both timely actionable insights and longer-term fundamental information. Anecdotal evidence suggests that these services are highly valued by institutional money managers (e.g., Alpha 2005). Yet, to our knowledge, Table 3, which reports that the median analyst makes 120 client calls per month (i.e., around 5–6 calls per weekday), is the first systematic evidence on the prevalence of these activities from the perspective of a sell-side analyst. This statistic is noteworthy as it indicates that analysts are in near constant contact with client investors and that this communication occurs outside of the eyes of academics and the general public.

Concierge Services. As part of their regular activities, analysts provide clients with selective access to the managers of covered companies. Like high-touch meetings, these communications are generally scheduled well in advance and often involve significant travel time. They are thus poorly suited to imparting timely, trade-relevant information. As part of its analyst evaluation and development process, the bank generates a single-dimensional score based on analysts' participation in these activities. As reported in Table 3, this score is non-zero in 57% of analyst-months (Panel A) and 100% of analyst-six-monthly observations (Panel B), indicating that, collectively, these events are relatively common. The specific services within this broader categorization include conferences, non-deal road shows, field trips, and management meetings.[18]

Conferences. During the sample period, the bank held around five annual conferences for large investors. These were concentrated in major money-centers (e.g., Boston, New York, and San Francisco), ranged in length from one to four days, and included presentations from as few as 50 to as many as 200 public and private firms (consistent with statistics reported by Markov et al. 2011). Each presenting company would be scheduled for 30 minutes, including time for a management presentation and questions. Because analysts participate in the same regularly scheduled conference(s) year after year, we do not expect a significant within-analyst relation between conferences and our analyst franchise proxies.[19] Instead, we expect analysts with stronger franchises to host more conference sessions. We discuss this point in greater detail in Section VI. As reported in Table 3, in 14% of analyst-months (Panel A) and 71% of analyst-six-monthly observations (Panel B), analysts moderated a conference session for at least one of their covered companies.

Non-Deal Road Shows (a.k.a. "investor office meetings"). Sell-side analysts often play a part in non-deal road shows that allow for one-on-one meetings between corporate managers and buy-side clients over one or more days. According to investor relations (IR) professionals, "the non-deal road show is the most effective forum to develop interest in a stock because the

[18] Points assigned to the main categories are as follows: conferences = 3 points for each presenting company; non-deal road shows = 9 points per day; field trips = 12 points per event; meals with corporate executives = 3 points per meal.

[19] Using analyst-firm-level data, Green et al. (2011, 44) find changes in conference activity to explain approximately fourteen one hundredths of one percent of the variation in broker share of trade execution in analysts' covered stocks.

portfolio manager can ask questions, look management in the eye, and share concerns in a private setting" (Ryan and Jacobs 2005, 205). Five to eight 45–60 minute meetings are typically scheduled per day. The events are held at the offices of current and potential investors and therefore generally occur in major money centers. Although sell-side analysts help to facilitate these events and accompany managers on their travels to investor offices, they do not usually participate in the meetings themselves.[20] As reported in Table 3, analysts took companies on the road in 36% of the sample months, which required them to be away from the office for between one (10^{th} percentile) and four (90^{th} percentile) days.

Field Trips (a.k.a. "reverse roadshows"). Analysts also take institutional investors to covered companies' headquarters and production and distribution facilities. Sometimes a series of short site visits is organized as a one or two day tour. Descriptive statistics reported in Table 3 indicate that analysts host a field trip in 9% of months (i.e., a typical analyst hosts around one field trip per year).

Management Meetings (a.k.a. "meals with managers"). In conjunction with many of their formal management-access events (i.e., conferences and field trips), analysts often arrange smaller, private gatherings for buy-side and company managers, typically (around 90% of the time) involving meals (breakfasts, lunches, dinners). As reported in Table 3, 16% of analyst months (Panel A) and 60% of analyst-six-monthly observations (Panel B) involve at least one analyst-hosted management meeting.

[20] For example, according to the former director of U.S. research for Capital Guardian Trust Co., "A lot of investors leave the analyst or the salesperson at the door. . . . If we think it's an important meeting, we'll ask them to wait outside, too, because we can pick up a lot more information without them. . . . As a general practice, Fidelity Investments discourages sell-side analysts from attending meetings during non-deal road shows. American Century Investments, Prudential Investments, and Putnam Investments are just a few of the firms that do the same" (Institutional Investor 2000).

Other Concierge Services. Analysts occasionally engage in other forms of client-service activity, including in-house access events (events that include more than one covered company are often referred to as in-house conferences), retreats (e.g., fishing or golfing trips), meetings at major sporting events (e.g., box seats at a Yankees' game), and informational sessions (often in the form of a conference call). Because these services are relatively infrequent, we aggregate them into a single variable using the set of weights supplied by the bank (see footnote 18). As reported in Table 3, only 9% of months and 32% of six-monthly observations involve one such event.

Association Tests

Table 4 presents Pearson correlations between pairs of client-service and analyst-franchise variables. Associations above (below) the main diagonal reflect semiannual (month-to-month) changes.

Given our finding that broker votes best reflect the information used to assess analysts' franchises during compensation-award decisions, our primary focus are the pairwise service-voting correlations reported in the rightmost column. We observe a significant positive association between changes in broker votes for a given analyst and changes in the analyst's supply of published research (notes, reports and forecasts), high-touch services (client meetings and private phone calls), and certain concierge services (non-deal road shows and other concierge services). Notably, the largest correlation is observed for private phone calls (0.44, $p < 0.001$), a previously unexplored client-service channel. That this variable alone explains approximately 20% of the intertemporal variation in clients' votes is noteworthy given that the frequency of analysts' forecasts—i.e., the variable that prior research indicates to be most strongly associated with analyst ratings (Stickel 1992)—explains a mere 4% of the intertemporal variation in clients' votes.[21]

To better understand the cause of the relatively weak relations between analyst-compensation-award decisions and our two transactions-based franchise metrics, we next investigate the informational overlap between changes in these franchise measures and changes in analysts' client-service activity. Our investigation is motivated by Holmström's (1979) informativeness principle, which states that a measure's usefulness for evaluation and reward decisions is increasing in the measure's ability to reflect valued actions.

Consistent with this hypothesis and the compensation results reported in Section IV, the evidence in Table 4 indicates that commissions from analysts' covered stocks and the broker share of trade execution in analysts' covered stocks are largely uninformative about the valued actions reflected in analyst ratings. First, the pairwise Pearson correlations reported in the second-to-last column show that semiannual changes in the natural logarithm of commissions from analysts' covered stocks are not significantly associated with contemporaneous changes in any client service. Second, the associations in the third-to-last column indicate that semiannual changes in the broker share of trade execution in analysts' covered stocks are not significantly associated with contemporaneous changes in published research or high-touch service; and, for concierge services three of the associations are statistically negative (i.e., of the opposite sign). The monthly data reported in the bottom two rows of Table 4 present a marginally better picture. Using this narrower evaluation window, we find changes in commissions from covered stocks

[21] This latter result is broadly consistent with prior research on the determinants of analyst ratings (e.g., Stickel 1992; Jackson 2005; Emery and Li 2009).

and the broker share of trade execution in covered stocks to be positively associated with analysts' more timely client services—i.e., high-touch phone calls and notes (and the forecasts therein)—but not less timely services like reports, high-touch meetings, or concierge services.

Of course, in order to explore the implications of changes in individual client services for the dynamics of analysts' franchises it is important that changes in other client services be held constant. Yet as one would expect if analysts combine services in a complementary fashion, we detect positive associations among several channels of activity (particularly in the monthly data reported below the main diagonal). For example, we find the use of private telephone calls and note production to be positively correlated, consistent with the view that analysts combine these channels in a mutually reinforcing (i.e., complementary) fashion.[22] Consequently, the positive association between, say, broker votes and research notes may simply reflect changes in effort broadly defined, as opposed to effort specifically directed toward the production of research notes.

Equally interesting, Table 4 also documents *negative* associations among several pairs of client-service variables. For example, consistent with the hypothesis that time-consuming out-of-office services (e.g., non-deal road shows and conferences) incur sizable informational opportunity costs, we find month-to-month changes in these variables to be negatively associated with changes in published research and more traditional forms of client service. These findings suggest that analysts' incentives are a function of not only their formal compensation structures (Groysberg et al. 2011), career concerns (Mikhail et al. 1999; Hong and Kubik 2003), and desire

[22] This pattern is consistent with Goldstein et al.'s (2009, 5193) assertion that top clients demand "elaboration from the analyst on the brief First Call note to ascertain the value of the analyst's information."

to curry favor with corporate managers (Francis and Philbrick 1993), but also the opportunity costs inherent in the client-service environment in which they are embedded.

Given the non-zero correlations among several pairs of client-service variables, inferences from simple correlations may be misleading. Table 5 therefore reports results from the following empirical model estimated on our sample of 132 first-differenced, semiannual analyst observations:

$$Broker\text{-}Vote\ Signal_{i,t} - Broker\text{-}Vote\ Signal_{i,t-1} = \alpha_t + \sum_{j=1}^{J} \beta_j \left(Channel_{i,j,t} - Channel_{i,j,t-1} \right) + \varepsilon_{i,t}$$

where the subscripts *i, j,* and *t* denote analyst *i,* client-service channel *j*, and semiannual period *t*, respectively.[23] This estimated β statistics enable us to infer the average incremental effect of each client service holding other client-service activity constant; and the estimated R^2 statistic enable us to infer the implications of client-service effort, broadly defined, for the dynamics of analyst ratings (and thus the signal-to-noise ratio of these ratings).

Several results are noteworthy. First, column 1 documents a positive and statistically significant ($p < 0.001$) association between changes in broker votes and changes in concierge services. Column 2 shows that this association is driven primarily by non-deal road shows and field trips to covered companies: the coefficient on non-deal road shows is 0.285 ($p = 0.002$), indicating that an additional day of non-deal road shows is associated with a 0.29% increase in cumulative votes (e.g., from 50% to 50.29%); the coefficient on tours is 0.70 ($p = 0.065$),

[23] The broker-vote signal is a proportion, and thus bounded by 0 and 100. For ease of interpretation and because the values do not approach either extreme, we opted for the simple functional form shown above. As a robustness test, we examined the change in the logit-transformed broker-vote signal (i.e., ln[B.V.S/{1–B.V.S}]) as a dependent variable. Our inferences remained unchanged.

implying that a site visit to the facilities of a covered company (or set of related companies) is associated with a 0.70% increase in cumulative votes.

Second, column 1 documents a positive and statistically significant association between changes in high-touch services and favorable broker-voting outcomes ($p < 0.001$). As reported in column 2, this association is driven by both forms of high-touch service: the coefficient on phone calls is 0.012, which indicates that an additional call is associated with a 0.012% increase in cumulative votes; the coefficient on face-to-face meetings is three to four times as large, implying that an additional meeting is associated with a 0.046% increase in cumulative votes.

Third, column 1 documents a positive and statistically association between published research and broker votes ($p < 0.05$). Column 2 indicates that this relation is driven by whitepapers: we find an additional whitepaper to be associated with a 1.77% increase in cumulative votes (e.g., from 50% to 51.77%). That this magnitude is equivalent to approximately three tour days, six non-deal road show days, forty high-touch meetings, or 140 phone calls, is noteworthy; indeed, it suggests that, despite being non-timely and vulnerable to significant public-goods problems, whitepapers are an important vehicle through which analysts signal their industry knowledge and build and sustain their franchise. It also highlights the importance of analyst-level data to our investigation, as whitepapers do not pertain to an individual stock, but rather broader multi-stock themes. Interestingly, blast voicemails also load significantly, suggesting that promotion of high-conviction ideas helps analysts to strengthen their networks of client relationships.

Fourth, column 2 indicates that changes in analysts' client-service efforts, broadly defined, explain nearly fifty percent of the intertemporal variation in broker-voting outcomes.[24] Recall from Table 4 that changes in high-touch telephone calls (earnings forecasts) explain around twenty percent (four percent) of the intertemporal variation in broker-voting outcomes. Incorporating the information in the other client-service variables thus contributes to an approximate two-and-a-half-fold (thirteen-fold) increase in the explanatory power of client-service effort for analyst ratings when benchmarked against phone calls (earnings forecasts) alone.

That simple changes in the frequencies of analysts' various client-service efforts explain around half of the variation in institutional investors' voting decisions has important implications for understanding of analysts' economic incentives and behavior. Not only does this result provide compelling evidence that changes in client-service effort, broadly defined, explain the dynamics of analysts' franchises (and thus compensation), it stands in stark contrast to recent claims that analyst ratings are popularity contests whose outcomes are disconnected from analyst action (e.g., Emery and Li 2009; Extel 2011; Gresse and Porteau de la Morandière 2014). Indeed, our results are more consistent with the view that analyst ratings provide sell-side firms with an informative output-based metric to incentivize a broad range of client-service actions.

Of course, it is worth noting that analyst ratings also appear to reflect changes in market interest in analysts' covered stocks for reasons orthogonal to analyst behavior. Column 3 documents that after controlling for analysts' client-service efforts, changes in the natural logarithm of trading activity in analysts' covered stocks (as measured by CRSP and Datastream) are associated with changes in broker-voting outcomes. We interpret these results as consistent

[24] The period fixed effects explain approximately 10% of the intertemporal variation in broker-voting outcomes.

with broker votes responding to market interest in an analyst's covered stocks for reasons outside an analyst's control. Nevertheless, the effect of analyst effort clearly dominates. For example, unreported tests indicate that adding the client-service variables to a baseline model that includes changes in the natural logarithm of trading in analysts' covered stocks (as measured by CRSP) and time effects increases the R^2 by approximately 0.3 (i.e., 30%). In contrast, adding changes in the natural logarithm of CRSP volume to a baseline model that includes the client-service variables and time effects increase the R^2 by around 0.02 (i.e., 2%).[25]

Tables 6 and 7 present analogous analyses for our two transaction-based franchise variables. For brevity, we report results using monthly (as opposed to semiannual) changes. The pattern mirrors that depicted by the pairwise associations reported in Table 4. Moreover additional (unreported) analyses indicate that adding the client-service variables to a baseline commission model that includes changes in the natural logarithm of CRSP volume and time effects increases the R^2 by less than 0.03 (i.e., 3%). Taken as a whole, we interpret these results and those reported in Section V as consistent with Holmström's (1979) informativeness principle: unlike broker votes, transactional measures of analysts' franchises have low signal to noise ratios and appear to receive little weight during analyst-evaluation-and-reward decisions.

In summary, the evidence in Sections IV and V yield the following insights. In a typical semiannual performance-evaluation period, the average analyst supplies around 80 research notes and three reports; spends around one week brokering meetings between client investors and corporate managers; and holds approximately 750 private phone calls and 45 one-on-one meetings with client investors. Changes in these client-service actions explain approximately

[25] Our inferences are unchanged when we drop the time effects. Without these controls, the estimated increase in R^2 is 2.3%. With these controls, it is 1.8%.

fifty percent of the intertemporal variation in broker votes, a mechanism used to measure the value that client investors ascribe to maintaining continued analyst relations, with the strongest sensitivity observed for widely disseminated, thematic, research reports known as whitepapers. Analysts' client-service actions, however, explain relatively little intertemporal variation in commissions and broker share of trade execution in their covered stocks. Finally, analysts who strengthen their client networks reap significant rewards and, consistent with the informativeness principle, we find these incentives to be delivered primarily through broker votes, not trades executed in analysts' covered stocks.

VI. ADDITIONAL TESTS

The Implications of Franchise-Management Concerns for Analyst Behavior

Our primary tests are consistent with the hypothesis that analysts face strong franchise-management incentives and that these incentives are primarily supplied through analyst ratings known as broker votes. An additional implication of this hypothesis is that analysts should respond predictably to these inferred incentives.

Because the weight applied to a client's votes during the franchise-evaluation process is contingent on the importance of that client, we posit that franchise-management concerns will create an incentive for analysts to favor larger, more important clients. To test this prediction, we use the supplemental telephone calling data obtained from the bank for the first three quarters of 2007. These data record the number of telephone calls made by each analyst to each of bank's voting clients by month. As expected, our results (unreported) indicate that large clients, whose votes are ascribed greater weight during the franchise-evaluation process, receive a disproportionate share of private telephone calls. For example, 36% (12%) of all calls were made to just ten (two) of the bank's more than 800 clients.

The Relation between Broker Votes and Brokerage Revenues

Our discussions with buy- and sell-side practitioners indicate that as part of their periodic commission-budgeting and order-allocation routines, buy-side institutions use broker votes to set commission targets for each broker. Consistent with Goldstein et al.'s (2009) aggregate-payment hypothesis, practitioners indicate that this process generally occurs at the brokerage level (i.e., not at the analyst- or analyst-firm level). However, because broker votes are used primarily as a means of determining what *share* of commissions each broker should receive (as opposed to how *much* commissions each broker should receive), practitioners indicate that the relation between changes in votes from a particular client and changes in brokerage revenues from that client is far from perfect (see, for example, Extel 2011; Balarkas 2013).

To shed some light on the strength of the voting-commission relation, we exploit supplemental voting and commission data for 54 of the sample firm's institutional clients (e.g., AllianceBernstein, Citadel, Fidelity, and Wellington) collected during the 2004–2006 period. Each client-year observation contains values for (i) total commissions the sample bank received from the client during the calendar year, aggregated across all stocks including those without analyst coverage, and (ii) the average voting outcome, expressed as the total number of votes cast for all of the bank's analysts divided by the maximum possible number of votes, as illustrated in the rightmost column of Figure 1.

Consistent with the insights gleaned from our practitioner interviews, our archival data indicate that brokerage commissions can be viewed as an endogenous outcome of the broker-voting process. Specifically, we find the correlation between changes in votes and changes in one-year-ahead log commissions to be 0.34 ($p < 0.01$).[26] Changes in clients' perceptions of a bank's analysts thus explain about one eighth of the variation in the percentage change in their commission payments to the bank as a whole.

Between-Analyst Association Tests

Given our focus on analysts' relational incentives, our primary interest is whether and how strongly the various actions that analysts take to serve client investors are related to the dynamics of their franchises. Accordingly, to prevent cross-sectional differences in ability and industry coverage from confounding our inferences, our within-analyst tests use each analyst as her own control for these differences.

A different, but nevertheless interesting, question is whether persistent cross-sectional differences in analysts' franchises can be "explained" by similarly persistent cross-sectional differences in analyst characteristics. To shed light on this question, this section examines pairwise between-analyst associations, computed from time-series averages of all observations for a given analyst (e.g., Groysberg et al. 2011).

For brevity, the results are not tabulated. However, several points are noteworthy. First, analysts with stronger franchises, as measured by broker votes, are significantly more productive

[26] The correlations between changes in votes and contemporaneous and lagged changes in log commissions are 0.10 and 0.01, respectively (not significantly different from zero).

across a broad range of client services,[27] more likely to have been recognized by *Starmine* or the *WSJ* for the quality of their forecasts and recommendations, and more likely to be managing directors (i.e., the most senior and valued members of the bank). Second, we observe a similar, but markedly weaker, pattern when the natural logarithm of commissions from covered stocks is substituted for broker votes. Finally, the broker share of trade execution in analysts' covered stocks continues to be low in signal and high in noise. However, we do detect one significant pattern in these data: analysts with persistently strong market share in their covered stocks consistently spend more time with corporate managers (as measured by non-deal road show days and conference participation). Yet we caution readers against interpreting these associations as evidence that non-deal road shows and conferences drive meaningful volume in analysts' covered stocks. Our discussions with practitioners indicate that the bulk of this relation is likely to reflect corporate managers' greater receptiveness to brokers who are the "axes" (i.e., important suppliers of liquidity) in their stock/industry-coverage space.

VII. CONCLUSION

Capital market participants indicate that the overriding objective of sell-side analysts is to build and protect their franchise. Scholarly understanding of how this construct is managed and best operationalized, however, is limited. Indeed, the lack of direct evidence on analysts' job and objective functions is believed to be a principal factor that "impedes our ability to further our understanding of sell-side analysts" (Bradshaw 2011, 39).

[27] These services include notes, high-touch phone calls and face-to-face meetings, as well as non-deal road shows, conferences, tours, and private meals with corporate managers.

The evidence in this paper contributes to understanding of how sell-side analysts build and sustain their franchises; the economic gains to successfully managing this challenge; and the metrics through which these incentives are delivered. We show that in a typical semiannual performance-evaluation period, the average analyst supplies around 80 research notes and three reports; spends around one week brokering meetings between client investors and corporate managers; and holds approximately 750 private phone calls and 45 one-on-one meetings with client investors. Changes in these client-service actions explain approximately fifty percent of the intertemporal variation in broker votes, a mechanism used to measure the value that client investors ascribe to maintaining continued analyst relations, with the strongest sensitivity observed for widely disseminated, thematic, research reports known as whitepapers. Analysts' client-service actions, however, explain relatively little intertemporal variation in commissions and broker share of trade execution in their covered stocks. Analysts who strengthen their franchises reap significant rewards and, consistent with the informativeness principle, we find these incentives to be delivered primarily through broker votes, not trades executed in analysts' covered stocks. Notably, we find no evidence that analyst compensation is related to the broker share of trade execution in analysts' covered stocks—a variable commonly used to proxy for the strength of analysts' client-service incentives and client relationships (e.g., Irvine 2004).

Our findings suggest that analyst ratings—and broker votes in particular—are an important and fruitful area for further scholarly inquiry. Recent work claims that these ratings are "popularity contests" (Emery and Li 2009) and "about as useful as a guide to sexual etiquette would be for Paris Hilton" (Extel 2011, 8).[28] Our findings, however, are more consistent with

[28] Even Stickel's seminal study (1992), which is commonly cited as the primary evidence that institutional investors assign higher ratings to analysts who provide superior client service, concludes that although there appears

the view that broker votes a key component of the investment-research industry's contracting technology. Specifically, the evidence in this paper suggests that institutional investors use broker votes to budget future aggregate commission payments across brokerage firms; that these votes are responsive to actions that brokerage-house analysts take to serve client investors; and that brokerage firms use these client-supplied votes as a quasi-allocation base to indirectly reward individual analysts for contributions to brokerage-wide commission payments. Our results thus suggest that broker-vote reporting is likely to function as the nexus for a set of multilateral relational contracts between sell-side brokers, their affiliated analysts, and their buy-side clients (Levin 2002).

In closing, we acknowledge that our study is subject to the usual caveats inherent in field-based research, most notably, generalizability. Our data, being from a single bank, should be interpreted with this in mind. In particular, because we examine a mid-sized bank, some of our findings may not be generalizable to analysts at bulge-bracket banks. Nevertheless, although the economic magnitudes documented in our study are likely to be partially dependent on bank scale, we are unaware of any context-specific interactions that would render our results invalid in other settings. Indeed, the practices at the sample bank closely mirror those at many other banks, ranging from bulge-bracket banks to other mid-sized brokers.[29] Of course, only future research can address this issue conclusively.

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to be a statistically significant relation between analyst ratings and analyst earnings forecasts, "there are reasons to question the economic significance" of this result (Stickel 1992, 1831).

[29] See, for example, Groysberg (2010), Groysberg and Healy (2013), and SEC (2013).

REFERENCES

Alpha. 2005. Ho hedge funds rate Wall Street analysts. November 21.

Baker, G. 1987. Discussion of "An analysis of the use of accounting and market measures of performance in executive compensation contracts" *Journal of Accounting Research* 25: 126–129.

Balarkas, R. 2013. Comment: Broking faces change from 'unbundling' effects. *Financial Times.* November 25.

Banker, R. and S. Datar. 1989. Sensitivity, precision, and linear aggregation of signals for performance evaluation. *Journal of Accounting Research* 27: 21–39.

Bradshaw, M. 2011. Analysts' forecasts: What do we know after decades of work? Working paper, Boston College.

Brochet, F., G. Miller, and S. Srinivasan. 2014. Do analysts follow managers who switch companies? An analysis of relationships in capital markets. *The Accounting Review* 89: 451–482.

Brown, L., A. Call, M. Clement, and N. Sharp. 2014. Skin in the game: The inputs and incentives that shape buy-side analysts' stock recommendations. Working paper, Temple University.

Brown, L., A. Call, M. Clement, and N. Sharp. 2015. Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research* (forthcoming)

Bull, C. 1987. The existence of self-enforcing implicit contracts. *The Quarterly Journal of Economics* 102: 147–160.

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

Cowen, A., B. Groysberg, and P. Healy. 2006. Which types of analyst firms are more optimistic? *Journal of Accounting & Economics* 41: 119–146.

Datar, S., S. Kulp, and R. Lambert. 2001. Balancing performance measures. *Journal of Accounting Research* 39: 75–92.

D'Antona, J. 2011. Gotta have it!: Research's growing importance as commissions decline. *Traders Magazine* (February). Available at: http://www.tradersmagazine.com/issues/24_319/research-brokerage-commissions-corporate-access-volume-trading-107149-1.html.

De Franco, G. and Y. Zhou. 2009. The performance of analysts with a CFA designation: The role of human-capital and signaling theories. *Accounting Review* 84: 383–404.

De Franco, G., and O. Hope. 2011. Do analysts' notes provide new information? *Journal of Accounting, Auditing & Finance* 26: 229–254.

Denlinger, K. 1977. King Albert no franchise but a national jewel; Long reign expected of king. *The Washington Post*. November 30.

Eccles, R. and D. Crane. 1988. *Doing deals: Investment banks at work.* Boston, MA: Harvard Business School Press.

Emery, D. and X. Li. 2009. Are the Wall Street analyst rankings popularity contests? *Journal of Financial and Quantitative Analysis* 44: 411–437.

Ertimur, Y. W. Mayew, and S. Stubben. 2009. Analyst reputation and the issuance of disaggregated earnings forecasts to I/B/E/S. *Review of Accounting Studies* 16: 29–58.

Extel. 2011. Buyside broker reviews—Commission or omission? The brokers' perspective.

Francis, J. and D. Philbrick. 1993. Analysts' Decisions as products of a multi-task environment. *Journal of Accounting Research* 31: 216–231.

Frankel, R., S. Kothari, and J. Weber. 2006. Determinants of the informativeness of analyst research. *Journal of Accounting & Economics* 41: 29–54.

Goldstein, M., P. Irvine, E. Kandel, and Z. Wiener. 2009. Brokerage commissions and institutional trading patterns. *Review of Financial Studies* 22: 5175–5212.

Green, T., R. Jame, S. Markov, and M. Subasi. 2011. Investor conferences as a research service. Working paper, Emory University (December).

Green, T., R. Jame, S. Markov, and M. Subasi. 2014a. Broker-Hosted Investor Conferences. *Journal of Accounting & Economics* 58: 142 –166.

Green, T., R. Jame, S. Markov, and M. Subasi. 2014b. Access to management and the informativeness of analyst research. *Journal of Financial Economics* 114: 239–255.

Gresse, C. and L. Porteau de la Morandière. 2014. Rising and senior stars in European financial analyst rankings: The talented and the famous. Working paper, Universitè Paris-Dauphine.

Groysberg, B. 2010. *Chasing stars: The myth of talent and the portability of performance.* Princeton, NJ: Princeton University Press.

Groysberg, B., P. Healy, and D. Maber. 2011. What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research* 49: 969–1000.

Groysberg, B. and P. Healy. 2013. *Wall Street Research: Past, Present and Future.* Stanford, CA: Stanford University Press.

Gu, Z., L. Zengquan, and Y. Yang. 2013. Monitors or predators: The influence of institutional investors on sell-side analysts. *The Accounting Review* 88: 137–169.

Holmström, B. 1979. Moral hazard and observability. *Bell Journal of Economics* 10: 74–91.

Holmström, B. and P. Milgrom. 1991. Multitask principal-agent analyses: incentive contracts, asset ownership, and job design. *Journal of Law, Economics & Organization* 7: 24–52.

Hong, H. and J. Kubik, and A. Solomon. 2000. Security analysts' career concerns and herding of earnings forecasts. *RAND Journal of Economics* 31: 121–144.

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

Institutional Investor. 2000. The 2000 All-America Research Team. *Institutional Investor* (Americas edition) 34 (10): 57–162.

Irvine, P. 2004. Analysts' forecasts and brokerage-firm trading. *The Accounting Review* 79: 125–149.

Jackson, A. 2005. Trade generation, reputation, and sell-side analysts. *Journal of Finance* 60: 673–717.

Juergens, J., and L. Lindsey. 2009. Getting out early: An analysis of market making activity at the recommending analyst's firm. *Journal of Finance* 64: 2327–2359.

Kini, O. S. Mian, R. Rebello, and A. Venkateswaran. 2009. On the structure of analyst research portfolios and forecast accuracy. *Journal of Accounting Research* 47: 867–909.

Lang, M. 2008. Discussion of "Analyst coverage and the cost of raising equity capital: evidence from underpricing of seasoned equity offerings" *Contemporary Accounting Research* 25: 701–706.

Leone, A. and J. Wu. 2007. What does it take to become a superstar? Evidence from institutional investor rankings of financial analysts. Working paper, University of Rochester.

Levin, J. 2002. Multilateral relational contracting and the employment relationship. *Quarterly Journal of Economics* 117: 1075–1103.

Levin, J. 2003. Relational incentive contracts. *American Economic Review* 93: 835–857.

Ljungqvist, A. F. Marston, L. Starks, K. Wei, and H. Yan. 2007. Conflicts of interest and the moderating role of institutional investors. *Journal of Financial Economics* 85: 420–456.

Markov, S., V. Muslu, and M. Subasi. 2011. Analyst tipping: Additional evidence. Working paper, University of Texas at Dallas.

McNichols, M. 1990. Discussion of analyst following and institutional ownership. *Journal of Accounting Research* 28: 77–82.

Michaely, R., and K. Womack. 1999. Conflicts of interest and the credibility of underwriter analyst recommendations. *The Review of Financial Studies* 12: 653–686.

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

Murphy, K. 1985. Corporate performance and managerial remuneration: an empirical analysis. *Journal of Accounting & Economics* 7: 11–42.

Niehaus, G., and D. Zhang. 2010. The impact of sell-side analyst research coverage on an affiliated broker's market share of trading volume. *Journal of Banking & Finance* 34: 776–787.

Oyer, P. 2004. Why do firms use incentives that have no incentive effects? *Journal of Finance* 59: 1619–1650.

Petersen, M. 2009. Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies* 22: 435–80.

Pfarrer, M., T. Pollock, and V. Rindova. 2010. A tale of two assets: The effects of firm reputation and celebrity on earnings surprises and investors' reactions. *Academy of Management Journal* 53: 1131–1152.

Reingold, D. and J. Reingold. 2006. *Confessions of a Wall Street analyst: The true story of inside information and corruption in the stock market*. New York, NY: HarperCollins.

Rindova, V., I. Williamson, A. Petkova, and J. Sever. 2005. Being good or being known: an empirical examination of the dimensions, antecedents, and consequences of organizational reputation. *Academy of Management Journal* 48: 1033–1049.

Ryan, T., and C. Jacobs. 2005. *Using Investor Relations to Maximize Equity Valuation.* Hoboken, NJ: John Wiley and Sons.

SEC. 2013. In the matter of Goldman, Sachs & Co: Administrative Proceeding File No. 3-14845. Securities and Exchange Commission. April 12. http://www.sec.gov/litigation/admin/2012/34-66791.pdf

Soltes, E. 2014. Private interaction between firm management and sell-side analysts. *Journal of Accounting Research* 52: 245–272.

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

Valentine, J. 2011. *Best Practices for Equity Research Analysts.* New York, NY: McGraw Hill.

Wallace, W. 1983. Stars show there 1, 2 punch. *The New York Times*. July 11.

Weisman, L. 1996. Today marks decline for teams to designate their 'franchise players' *USA Today*. February 15.

FIGURE 1

Informational Architecture of the Broker-Vote Reporting System: Period t

Client Weight	Client Name	Analyst 1: Adam Abramowitz	…	Analyst 30: Zach Zyleski	Client total	***Brokerage-wide scores***
4	C1 (Fidelity)	0	…	4	0 + … 4 = S_1	*100 ×* $[S_1 \div (150)]$
4	C2	3	…	4.5	3 + …. 4.5 = S_2	*100 ×* $[S_2 \div (150)]$
…	…	…	…	…		
…	…	…	…	…		
1	C54	2	…	5	2 + … 5 = S_{54}	*100 ×* $[S_{54} \div (150)]$
1	C55	5	…	4	5 + … 4 = S_{55}	*100 ×* $[S_{55} \div \boxed{(150)}]$
Analyst-level sum		0 + 12 +…2 + 5 = A_1	× 5	16 + 18 +… 5 + 4 = A_{30}		
Total potential points		20 + 20 +… 5 + 5 = P	…	20 + 20 +… 5 + 5 = P		
Analyst-level signal		*100 ×* $[A_1 \div P]$	…	*100 ×* $[A_{30} \div P]$		

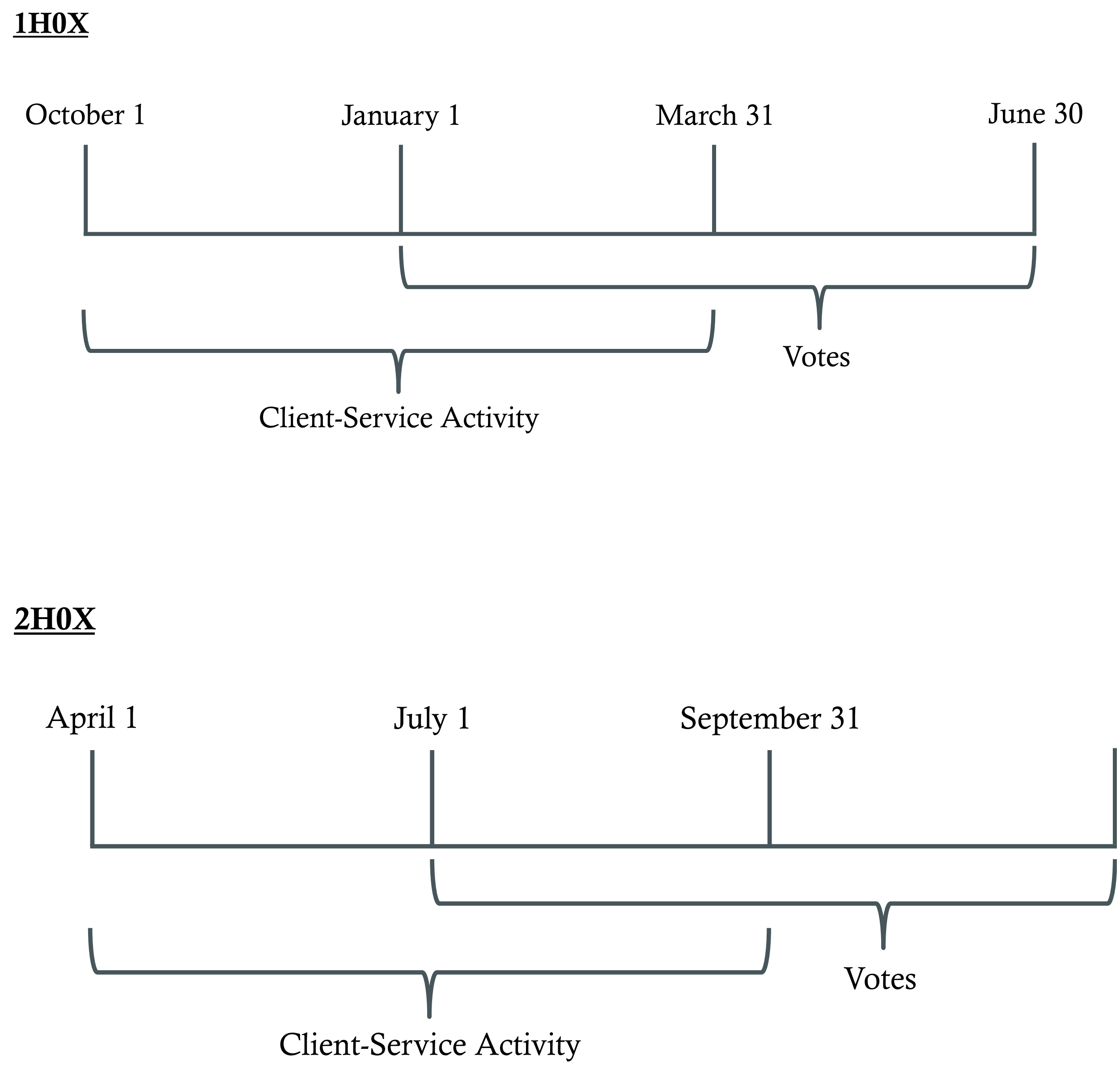
Maximum possible number of votes for the research department as a whole = 30 analysts × 5 votes per analyst = 150

Maximum possible points from a given client for a given analyst = Client weight × 5 votes per analyst

The figure illustrates the basic architecture of a broker-vote reporting system from the perspective of a sell-side broker dealer. Each row corresponds to a given buy-side client, with top clients appearing in the uppermost rows (Fidelity, for example, might be client "C1"). Each column corresponds to one of the broker's sell-side analysts, who are listed alphabetically (Adam Abramowitz, for example, might be Analyst 1). Each cell reports the votes awarded by a particular client to a particular analyst (standardized to a 0 to 5 scale). For example, the figure indicates that client C1 awarded 0 votes to analyst 1 and 4 votes to analyst 30. In computing the bottom line "analyst-level signals," the votes from top clients receive a greater weight than the votes from less important clients. The votes from client C1, for example receive a weight of 4 while the votes from client C55 receive a weight of 1. The total weighted number of votes received by a given analyst is reported in the "Analyst-level sum" row. Analyst 1, for example, received $(4 \times 0) + (4 \times 3) + \ldots + (1 \times 2) + (1 \times 5) = A_1$ votes. To convert this sum into a proportion, it is normalized by the total potential weighted votes. Analyst 1, for example could have received at most $(4 \times 5) = 20$ weighted votes from client C1 and $(1 \times 5) = 5$ weighted votes from client C55. Our primary tests use data gathered from the bottom line of this figure (i.e., the "analyst-level signals"). These data enable us to perform higher-powered and more nuanced tests and are consistent with prior research on sell-side analysts' broker-vote-based incentives (Groysberg et al. 2011). Our supplemental voting-commission test, which is reported in Section VI, uses data gathered from the rightmost column (i.e., the "brokerage-wide scores") because commission payments are generally set at the aggregate (i.e., brokerage-wide) level—not at the security or analyst level (Goldstein et al. 2009). These brokerage-wide scores are computed by aggregating the total number of votes awarded by a given client to the bank's sell-side research department to produce a "client total" that is, in turn, normalized by the maximum potential number of votes from the client. The maximum potential number of votes for the department as a whole is 5 votes per analyst multiplied by the number of analysts in the department. In the above stylized example, the maximum number of votes from a given client is 150.

FIGURE 2

The Measurement of Client-Service Activity and Analyst Ratings



This figure illustrates the voting and client-service windows for our primary dataset. Each year, the bank collects votes over two windows. The first tallies votes from January to June, the second from July to December. We compute the total client-service activity for the six months beginning three months before the voting window. Thus, votes from the first (second) window are matched to communication activity from October to March (April to September).

TABLE 1

Characteristics of Sample Analysts: Analyst-Year Data

	Mean	Median
Age (in years)	36.7	35
Years of experience as a senior sell-side analyst	6.3	5.0
Has a MBA degree	70%	1
Has a CFA designation	31%	0
Has been recognized by *Institutional Investor* at some point in career	11%	0
Has been recognized by *Starmine* at some point in career	22%	0
Has been recognized by the *Wall Street Journal* at some point in career	22%	0
Salary	\$149,556	\$124,375
Salary and Bonus	\$511,303	\$525,000

This table reports annual summary statistics for analysts employed by a mid-to-large-sized investment bank during the years 2004–2006 (N = 83).

TABLE 2

The Relation between Analyst Compensation and the Three Analyst Franchise Variables

Panel A: Analyst Compensation and Voting Outcomes—Levels

		Salary & Bonus	
	N	Mean	Median
Bottom third of the voting distribution	28	\$413,938	\$358,438
Middle third of the voting distribution	27	\$504,968	\$500,000
Top third of the the voting distribution	28	\$614,777	\$602,500

Correlation between Ln(salary & bonus) and votes awarded to analyst: 0.727, $p < 0.001$

Panel B: Analyst Compensation and Commissions from Covered Stocks— Levels

		Salary & Bonus	
	N	Mean	Median
Bottom third of the commissions distribution	28	\$441,621	\$419,063
Middle third of the commissions distribution	27	\$537,209	\$550,000
Top third of the commissions distribution	28	\$556,004	\$549,375

Correlation between Ln(salary & bonus) and Ln(commissions from covered stocks): 0.337, $p = 0.001$

Panel C: Analyst Compensation and Share of Volume in Covered Stocks— Levels

		Salary & Bonus	
	N	Mean	Median
Bottom third of the trading-share distribution	28	\$500,424	\$512,500
Middle third of the trading-share distribution	27	\$539,663	\$491,250
Top third of the trading-share distribution	28	\$494,835	\$548,750

Correlation between Ln(salary & bonus) and share of trading volume in covered stocks: 0.024, $p = 0.830$

Panel D: First-Differenced Regression Results

	Change in Ln(Salary & Bonus)							
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	***p*-Val.**	**Coeff.**	***p*-Val.**	**Coeff.**	***p*-Val.**	**Coeff.**	***p*-Val.**
Change in votes awarded to analyst	**1.039**	**0.002**					**0.885**	**0.012**
Change in log commissions from covered stocks			**0.130**	**0.024**			**0.096**	**0.101**
Change in share of trading volume in covered stocks					-0.852	0.765	-0.016	0.392
Year fixed effect	Yes		Yes		Yes		Yes	
R^2	21%		14%		4%		27%	
N	49		49		49		49	

This table examines the relation between analyst compensation and three franchise measures: analyst ratings known as broker votes, commissions from covered stocks, and the bank's share of trading volume in analysts' covered stocks. Panels A through C examine the relation between the level of analyst compensation and the levels of each of the three franchise metrics (N = 83). Panel D examines the relation between changes in analyst compensation and changes in the three franchise metrics (N = 49). Boldface type highlights statistical significance at the 10% level (based on a two-tailed test). Significance levels are based on heteroskedasticity-robust standard errors clustered by analyst and time (Petersen 2009) and test the null hypothesis that the respective coefficient is zero.

TABLE 3

Summary Statistics: Client-Service Activity

Panel A: Monthly Data

	Non-zero months (% of obs.)	Distribution of non-zero obs.				
		10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
Published Research:	100%					
No. of notes	100%	6	9	12	17	22
No. of reports	23%	1	1	1	4	4
No. of ordinary reports	20%	1	1	1	4	4
No. of whitepapers	3%	1	1	1	1	1
No. of blast voicemails used to promote research	16%	1	1	1	2	3
Components of Published Research:						
No. of initiations	18%	1	1	1	2	3
No. of new EPS forecasts	97%	2	3	5	8	10
No. of recommendation upgrades or downgrades	24%	1	1	1	1	2
High-Touch Services:	100%					
No. of client telephone calls	100%	47	85	120	165	210
No. of one-on-one meetings between analyst and client investors	71%	4	4	8	16	24
Concierge Services:	57%					
No. of non-deal-roadshow days	36%	1	1	2	3	4
No. of covered companies presenting at analyst-hosted conference	14%	1	3	5	9	13
No. of field trips to the facilities of covered companies	9%	1	1	1	1	1
No. of analyst-hosted management access meetings	16%	1	1	1	1	2
No. of points from other concierge services	9%	3	3	6	12	12

Panel B: Semiannual Data

	Non-zero periods (% of obs.)	Distribution of non-zero obs.				
		10th Pctl	25th Pctl	Median	75th Pctl	90th Pctl
Published Research:	100%					
No. of notes	100%	50	61	77	94	116
No. of reports	49%	1	1	2	7	19
No. of ordinary reports	41%	1	2	3	9	22
No. of whitepapers	13%	1	1	1	1	1
No. of blast voicemails used to promote research	38%	1	1	3	5	10
Components of Published Research:						
No. of initiations	70%	1	1	2	3	4
No. of new EPS forecasts	100%	21	26	32	38	43
No. of recommendation upgrades or downgrades	79%	1	1	2	3	5
High-Touch Services:	100%					
No. of client telephone calls	100%	419	609	749	915	1,071
No. of one-on-one meetings between analyst and client investors	98%	16	32	44	57	76
Concierge Services:	100%					
No. of non-deal-roadshow days	91%	1	3	4	8	10
No. of covered companies presenting at analyst-hosted conference	71%	2	4	7	11	15
No. of field trips to the facilities of covered companies	36%	1	1	1	2	3
No. of analyst-hosted management access meetings	60%	1	1	2	3	4
No. of points from other concierge services	32%	3	3	12	12	18

This table reports summary statistics for client-service activity for analysts employed by a mid-to-large-sized investment bank during the years 2004–2007. Panel A reports monthly statistics (N = 1,414). Panel B reports semiannual statistics (N = 170).

TABLE 4
Correlation Structure: Pairwise Changes

		Published Research						H-T Service		Concierge Service							
		I.	**II.**	**III.**	**IV.**	**V.**	**VI.**	**VII.**	**VIII.**	**IX.**	**X.**	**XI.**	**XII.**	**XIII.**	***Vol. Share***	***Log Commis.***	***Broker Votes***
Published Research:																	
I.	No. of notes		0.04	**0.18**	0.02	**0.24**	0.05	**0.38**	0.02	0.13	**-0.17**	**0.18**	**-0.16**	**0.23**	0.05	0.05	**0.31**
II.	No. of reports	**-0.07**		-0.04	-0.07	0.01	0.08	**0.20**	0.03	-0.06	0.12	-0.11	**0.16**	0.02	-0.09	-0.02	**0.16**
III.	Promotion through blast voicemails	0.01	**0.08**		-0.02	0.04	0.02	-0.04	0.00	0.01	**-0.22**	-0.13	-0.04	-0.10	0.06	0.13	0.05
Components of Published Research:																	
IV.	No. of initiations	**0.07**	0.00	0.04		0.07	-0.09	0.01	-0.01	0.02	-0.14	0.08	**-0.15**	-0.08	-0.04	0.06	-0.14
V.	No. of new EPS forecasts	**0.80**	**-0.05**	**-0.05**	**0.08**		**0.19**	**0.23**	**0.17**	0.10	**0.19**	0.02	0.12	0.04	-0.06	0.01	**0.20**
VI.	No. of rec. upgrades or downgrades	**0.15**	0.01	**0.08**	-0.02	**0.10**		0.11	0.14	**-0.16**	0.04	**-0.17**	-0.10	-0.11	0.12	0.03	-0.01
High-Touch Services:																	
VII.	No. of client telephone calls	**0.38**	0.02	**0.11**	0.01	**0.28**	**0.08**		0.07	-0.03	**0.18**	0.01	**0.28**	**0.17**	0.11	0.01	**0.44**
VIII.	No. of one-on-one client meetings	**-0.13**	**-0.07**	0.02	0.02	**-0.12**	-0.03	**-0.09**		-0.06	**0.20**	-0.11	0.05	**-0.15**	**0.16**	0.12	**0.15**
Concierge Services:																	
IX.	No. of non-deal-roadshow days	**-0.10**	-0.03	**0.05**	-0.01	**-0.14**	-0.03	-0.02	**0.06**		0.03	0.12	**-0.16**	0.00	**-0.17**	0.03	**0.28**
X.	No. of covered conference firms	**-0.31**	0.00	-0.02	0.00	**-0.26**	-0.04	**-0.09**	0.04	-0.02		-0.04	**0.35**	-0.05	**-0.17**	0.04	0.08
XI.	No. of field trips	**-0.09**	-0.01	**0.05**	-0.04	**-0.12**	-0.02	-0.01	**0.06**	-0.01	0.01		0.03	-0.04	**-0.15**	-0.11	-0.01
XII.	No. of management access meetings	**-0.17**	0.01	0.02	0.03	**-0.17**	0.03	-0.03	**0.06**	**0.05**	**0.44**	0.04		-0.03	**0.20**	0.07	0.08
XIII.	No. of points from other concierge services	-0.04	0.01	-0.02	**-0.06**	-0.02	-0.03	**-0.08**	-0.01	**0.08**	**0.05**	0.00	**0.08**		-0.11	-0.12	**0.20**
Market share of volume in covered stocks		**0.11**	0.00	-0.04	0.02	**0.08**	0.03	**0.13**	0.02	0.01	-0.01	0.01	0.03	**-0.05**			
Log of commissions from covered stocks		**0.26**	-0.01	-0.01	0.02	**0.23**	**0.06**	**0.22**	0.00	-0.03	**-0.08**	-0.02	-0.02	**-0.06**			

This table reports pairwise Pearson correlations for changes in client-service activity and changes in the strength of analysts' franchises (as measured by the broker's share of trade execution in analysts' covered stocks, the natural logarithm of commissions from analysts' covered stocks, and analyst ratings known as broker votes). Associations below (above) the main diagonal are based on a sample of 1,369 monthly (132 semiannual) observations. Boldfaced type highlights statistical significance at the 10% level (based on a two-tailed test).

TABLE 5

Client-Service Activity and Changes in Broker Votes Awarded to Analysts

	Model 1		Model 2		Model 3	
	Coeff.	***p*-Val.**	**Coeff.**	***p*-Val.**	**Coeff.**	***p*-Val.**
Published Research:						
Published research (notes & reports)	**0.047**	**0.048**				
Notes			0.001	0.982	-0.002	0.956
Whitepapers			**1.774**	**0.006**	**1.603**	**0.011**
Other reports			0.083	0.471	0.080	0.472
Promotion of research via blast voicemails			**0.253**	**0.063**	**0.235**	**0.075**
High-Touch Service:						
Sum of personalized, private interactions	**0.012**	**<.001**				
Phone calls			**0.012**	**<.001**	**0.011**	**<.001**
One-on-one, face-to-face meetings			**0.046**	**0.002**	**0.047**	**0.002**
Concierge Service:						
Sum of concierge points	**0.025**	**<.001**				
Non-deal road shows			**0.285**	**0.002**	**0.269**	**0.002**
Conferences			0.028	0.500	0.030	0.468
Tours			**0.703**	**0.065**	**0.690**	**0.073**
Meetings			-0.012	0.957	-0.039	0.869
Other			0.063	0.261	0.069	0.212
Controls:						
Ln(CRSP volume of covered stocls)					**3.970**	**0.029**
Period fixed effects	Yes		Yes			
R^2	51%		57%		59%	
N	132		132		132	

This table reports results from regressing semiannual changes in broker votes on semiannual changes in client-service activity. Boldface type highlights statistical significance at the 10% level (based on a two-tailed test). Significance levels are based on heteroskedasticity-robust standard errors clustered by analyst and time (Petersen 2009) and test the null hypothesis that the respective coefficient is zero.

TABLE 6

Changes in Client-Service Activity and Changes in Log Commissions From Analysts' Stocks

	Model 1		Model 2		Model 3	
	Coeff.	*p*-Val.	Coeff.	*p*-Val.	Coeff.	*p*-Val.
Published Research:						
Published research (notes & reports)	**0.015**	**<.001**				
Notes			**0.016**	**<.001**	**0.012**	**<.001**
Reports			-0.014	0.627	-0.003	0.906
Promotion of research via blast voicemails			-0.017	0.521	-0.015	0.557
High-Touch Service:						
Sum of personalized, private interactions	**0.001**	**<.001**				
Phone calls			**0.001**	**<.001**	**0.001**	**<.001**
One-on-one, face-to-face meetings			0.001	0.655	0.001	0.657
Concierge Service:						
Sum of concierge points	-0.001	0.497				
Non-deal road shows			-0.013	0.215	-0.015	0.159
Conferences			0.004	0.503	0.006	0.314
Tours			0.014	0.713	0.011	0.780
Meetings			0.028	0.340	0.026	0.355
Other			**-0.014**	**0.022**	**-0.014**	**0.025**
Controls:						
Ln(CRSP volume of covered stocls)					**0.675**	**<.001**
Period fixed effects	Yes		Yes		Yes	
R^2	16%		17%		20%	
N	1,369		1,369		1,369	

This table reports results from regressing monthly changes in the natural logarithm of commissions from analysts' covered stocks on monthly changes in client-service activity. Boldface type highlights statistical significance at the 10% level (based on a two-tailed test). Significance levels are based on heteroskedasticity-robust standard errors clustered by analyst and time (Petersen 2009) and test the null hypothesis that the respective coefficient is zero.

TABLE 7

Changes in Client-Service Activity and Changes in Share of Volume in Analysts' Covered Stocks

	Model 1		Model 2	
	Coeff.	***p*-Val.**	**Coeff.**	***p*-Val.**
Published Research:				
Published research (notes & reports)	**0.018**	**0.011**		
Notes			**0.019**	**0.011**
Reports			-0.004	0.942
Promotion of research via blast voicemails			-0.081	0.128
High-Touch Service:				
Sum of personalized, private interactions	**0.002**	**<.001**		
Phone calls			**0.002**	**0.001**
One-on-one, face-to-face meetings			0.003	0.337
Concierge Service:				
Sum of concierge points	0.002	0.405		
Non-deal road shows			0.019	0.405
Conferences			0.002	0.851
Tours			0.037	0.639
Meetings			0.087	0.142
Other			**-0.028**	**0.025**
Controls:				
Period fixed effects	Yes		Yes	
R^2	8%		9%	
N	1,369		1,369	

This table reports results from regressing monthly changes in the broker share of trade execution in analysts' covered stocks on monthly changes in client-service activity. Boldface type highlights statistical significance at the 10% level (based on a two-tailed test). Significance levels are based on heteroskedasticity-robust standard errors clustered by analyst and time (Petersen 2009) and test the null hypothesis that the respective coefficient is zero.