ON THE PERFORMANCE OF FINANCIAL ANALYSTS

Byoung-Hyoun Hwang, Jose Maria Liberti and Jason Sturgess[1]

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We study the effect of information sharing and spillovers within organizations on individual productivity in the context of financial analysts. Using real firm mergers as a natural experiment we examine how exogenous variation in coverage of the target firm prior to the merger affects post merger performance for the analyst following the acquirer. We provide evidence that performance, measured as forecast error, decreases around the merger, and that the decrease is lower when the analyst's own brokerage also covers the target firm consistent with information spillovers affecting individual productivity. The effects of information spillovers are stronger when analysts share the same geographical location, when peers are of a greater quality, and for related mergers, but are lower when there are greater coordination costs. The findings suggest that human capital is portable but also that information spillovers within an organization might explain individual performance in knowledge-based industries, such as the financial industry.

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[1] First Draft: July 2013. Hwang is with the Dyson School of Applied Economics and Management, Cornell University, Warren Hall, Ithaca, NY 14853 and the Korea University Business School, Korea University, An-am, Seong-buk, Seoul, Korea 136-701. Liberti is with the Kellogg School of Management, Northwestern University, 2001 Sheridan Rd, Evanston, IL 60208 and the Kellstadt Graduate School of Business, DePaul University, One East Jackson Boulevard, Chicago, IL 60604. Sturgess is with the Kellstadt Graduate School of Business, DePaul University, One East Jackson Boulevard, Chicago, IL 60604. Email: bhwang@cornell.edu, j-liberti@kellogg.northwestern.edu and jsturge2@depaul.edu. We thank Marcin Kacperczyk (AFA discussant), Amit Seru, and seminar participants at the 2014 AFA meetings, DePaul University, Florida State University, Georgetown University, the University of Illinois at Chicago, and the University of Illinois at Urbana-Champaign for helpful comments.

1. Introduction

Since the seminal work of Coase (1937) economists have argued about the origins, role, and reasons of power in the theory of the firm. One line of argument in a long-standing debate on organizations is that ownership of physical assets is not the only source of power within the firm. Employees belong to an organization and the access that these employees have to a non-contractible critical resource such as knowledge in general, information, or the opportunity to work closely with peers may act as a mechanism to allocate power. In this context, the boundaries of the firm may become unclear in knowledge-based industries where the firm consists almost exclusively of human capital.

Knowledge-based industries, such as the financial, professional, academic, scientific and technical services industries, typically involve individual productivity within an organization. Thus, for most organizations, the observable product at the organization-level is the result of a conglomeration of inputs from many individuals and firm-level resources, making disentangling individual productivity challenging. Hart (1989) argues that, to the extent that there are complementarities across the tasks of employers, the total output of a group of workers may exceed the sum of the worker's individual output. Similarly, Klein (1988) distinguishes physical from human asset specificity by pointing out that an organization is embedded in the human capital of the employees at the firm but is greater than the sum of its parts. To address the question of power one needs to understand to what degree higher performing firms in these industries simply hire more productive individuals rather than successfully create high-productivity employees through their own firm-level resources. Further, if higher performing firms create high-productivity employees, what is the critical resource or channel that allows them to achieve this (Rajan and Zingales, (1998), (2001))? Does the individual performance increase because of better support, corporate culture, organizational capital or spillovers from more productive co-workers? Is physical proximity required for between employees to affect individual productivity?

The contribution of this paper is to evaluate whether higher performing organizations simply hire more productive individuals (*selection effect*) or if higher performing organizations create high-productivity individuals (*treatment effect*). Specifically, we are interested in whether the information environment offered by the organization affects individual performance in knowledge-based industries. We do so in the context of brokerage houses examining financial analyst productivity. Shedding light on the source and performance of financial analysts will allow us to make some progress on the fundamental question in economics as to whether the firm is more than the sum of its parts, and offer insight into the effects of information spillovers and specialization on individual productivity.

Identifying the treatment effect on individual productivity is inherently difficult for a few reasons. First, one needs to observe not only individual output but also be able to evaluate the level of output objectively. In asset-based industries, individual productivity has been examined for simple tasks where output and productivity are verifiable (for example, see the analysis of incentives and productivity using fruit-pickers in Bandiera, Barankay, and Rasul (2005)). However, in knowledge-based industries this is less straightforward because individuals working for a firm rarely produce output in their own name, and even where they do, it may not be easy to verify the quality of the output, or productivity. We overcome this hurdle by examining financial analysts where we can directly observe one of the most important performance outputs that financial analysts produce, namely earnings forecasts. We also have an objective benchmark, in the form of actual reported earnings, against which earnings forecasts can be compared. Thus, we can both observe individual productivity and also measure individual performance.

The second, and perhaps most challenging, obstacle to identifying the treatment effect on individual productivity is to separate selection effects from treatment effects. Complementarities imply that financial analysts should match on quality and brokers should contain analysts with similar skills and ability.[2] For example, consider two analysts where one works at Goldman Sachs and the second works at Cross Research, a small independent equity research firm based in New Jersey. It is likely that the nature of the information environment – teams, information sharing, organizational capital and technology – differs across the two brokerages. However, comparing the productivity of an analyst at Goldman Sachs with the productivity of an analyst at Cross Research compounds both selection and treatment. Observing

[2] See Becker (1973, 1981), Kremer (1993), Shimer and Smith (2000) among others, for a discussion of sorting, heterogeneous matching and the role of complementary tasks across individuals.

ex-post outcomes is not enough to disentangle whether the effect is coming from selection or treatment. Any difference in productivity might be due to the different treatment that an analyst receives from Goldman Sachs versus Cross Research, or equally might be due to differences in individual skill that resulted in one selecting into Goldman Sachs and the second selecting into a small independent equity research firm.

To separate treatment from selection, we exploit real firm mergers that create plausibly random variation in the information environment to examine individual productivity for the same individual working at the same brokerage organization. The appealing feature of this setting is that the decision of two firms to merge, which provides variation in information environment, is unlikely to be determined by the coverage or forecast accuracy of analysts covering the respective acquirer and target firm. Estimating results within broker-analyst ensures that matching between analyst and brokerage, i.e. selection effects, does not drive the results.

To illustrate our empirical methodology, consider the analyst working at Goldman Sachs. Selection explains the matching of the analyst with Goldman Sachs. The analyst's task is to specialize in one or more industries and follow one or more stocks. The information environment in which the analyst works likely varies from stock to stock – for example, some industries have larger teams that might facilitate greater information spillovers. Of course, neither the task nor structure of the information environment is random. Hence within analyst analysis alone is not sufficient to identify treatment. Real firm mergers provide exogenous variation in information environment. Mergers in which there is overlap in coverage of the target within the brokerage provide the treatment group, while those for which there is no overlap provide the control group. Examining differences between the treatment and control group within brokerage-analyst mitigates selection concerns because our inferences are made for the same analyst working for the same brokerage. Thus, any results we find can be attributed the treatment effect of variation in information environment or spillovers.

It is important to note that we are not studying the treatment effect of organization on the individual. Rather, we study the treatment effect of organization of information on individual productivity. Thus, we exploit plausibly random variation in the organization of information within the same brokerage house to understand the *causal* effects of information spillovers and information sharing on the productivity of financial analysts. To ensure that any results we find are not due to selection, we estimate the effect of variation in the information environment on changes in forecast error holding the broker-analyst relation constant.

We exploit variation in the real firm merger setting by classifying analysts into different types depending on the coverage of both acquirer and target firms. The overlap in coverage of the target may appear in two forms: the overlap exists because another analyst working at the same brokerage covers the target firm or, otherwise, the acquirer analyst also follows the target firm. We treat those analysts with no overlap as the benchmark counterfactual group in all our analysis. Our first set of within broker-analyst results show that differential analyst coverage of acquirer and target matters for performance relative to those analysts with no overlap. In particular, analyst performance is higher for those mergers in which analysts share information with a peer relative to the case where no information is shared. Interestingly, an analyst covering both the acquirer and target outperforms those situations where the overlap includes two different analysts. This results highlight that information may be lost in translation and the presence of communication and coordination costs across specialized analysts. Further, we rule out that the variation in performance we document across information type is not a determinant of analyst characteristics.

The amount of information spillovers may be correlated with both the organization capital and resources provided by the organization. For example, bigger and wealthier brokerage house may provide better information, technology and resources reducing communication costs across analysts. We explore variation across brokerage houses to study the degree of information spillovers. Results show that higher organizational capital is correlated with a differential increase in the performance of those analysts where transmission of information occurs relative to those analysts in which there is no overlap. Additionally, there is no such effect for those analysts that do not share any information among their peers since there are neither communication nor coordination costs.

The ability to transfer information across agents has implications for both the degree of spillovers and allocation of tasks in our setting. Radner (1993), Bolton and Dewatripont (1994), Aghion and Tirole (1997), Garicano (2000), Stein (2002), Garicano and Hansberg (2006) explore how organizational design and allocation of tasks affect the incentives to collect and use subjective or soft information. A central idea in this literature is that information sharing, particularly when information is soft or subjective in nature, becomes increasingly harder with both geographical and hierarchical distance.[3] We expect that the organizational design of the brokerage house, measured by the geographical location of analysts and team size, affects information spillovers. We find this is the case. While information spillovers increase average productivity, analysts perform better if information sharing originates from analysts in the same location, for which communication costs are lower.

There is also a cost to combining specialized employers. Communication and coordination costs may imply that the costs of coordinating a group of complementary specialized workers grow as the number of specialists in a team increases (Becker and Murphy (1992)). In our setting, coordination across an analyst that covers the target and another that covers the acquirer is more difficult if they are part of larger team. Our results highlight that analysts working in larger teams face greater communication and coordination costs, which limits the degree of information sharing and, concurrently, negatively impacts productivity.

A characteristic of certain knowledge-based production industries, such as equity analysts, is that individual productivity and reputation is also recognized and evaluated outside the boundaries of the firm. One potential concern is that our previous results are systematically driven by high skill and top-performing analysts (i.e., all-stars). Stars may be more skillful in dealing with real firm mergers and/or demand more attention and resources by virtue of the visibility they bring to the organization. We identify star analysts in the data and show that our previous results are not driven by the role of all-star equity

[3] In particular, Petersen and Rajan (2002), Mian (2006), Landier, Nair, and Wulf (2009), Liberti and Mian (2009), Agarwal and Hauswald (2010), Seru (2012), Liberti, Seru and Vig (2014), Gil, Liberti, and Sturgess (2014) and Skrastins and Vig (2015) study the effects of geographical and hierarchical distance on communication, production of information and firm-decision making.

analysts. We first show that all-star analysts have on average no impact on our main results. We also show that all-star status differentially increases productivity where the overlap is such that the analyst covering the acquirer is an all-star. The results on high-skill analysts suggest that all-star analysts are better able to capture information spillovers.

One may argue that information spillovers may be more or less important depending on the type of firm merger and whether the merger increases or decreases the uncertainty surrounding the earnings forecast. We explore how the information content of mergers impacts analyst productivity by focusing on whether the merger is in a related or unrelated line of business, and size of merger, which measures the size of the target relative to the acquirer. We are able to provide additional support for our main results. Overall, we find that information sharing across analysts has a positive effect on productivity when information is less costly to transmit (i.e., mergers are in related businesses) and when the benefits of sharing information are larger (i.e., target firm as a % of merged firm is large).

An additional concern is that the results on productivity may be driven by aggregate external information (i.e., information external to the firm). In particular, we study how outside target analyst coverage affects information spillovers. A few studies have examined how the aggregate information environment affects the demand for information production by analysts. For example, Lehavy, Li, and Merkley (2011) show that analyst following is greater for firms with less readable annual reports. Results show that external information spillovers are not confounding the average results on productivity, but also that spillovers may generate external to the firm as the information advantage of an analyst that covers both the acquirer and target decreases as the aggregate information environment strengthens. By demonstrating that the activity of analysts is impacted by information environment we connect to the empirical work on the boundaries of the firm.[4]

A final concern is the impact of specialization on productivity. It may possible that specialization absorbs the impact of information spillovers on productivity. We find this is not the case. In fact, specialization has a differential positive impact on productivity for those analysts where information

[4] Among others see Mullainathan and Scharfstein (2001), Beshears (2010), Bloom et al. (2010) and Seru (2012).

sharing exists. We conclude that specialization and spillovers are additive and that specialization increases the ability of analysts to coordinate and take advantage of information spillovers.

By utilizing the financial analyst industry as our setting, we also add to the literature on professional forecasters. Financial analysts play an integral role in financial markets. They collect, process, and transmit information to market participants, who in turn use analysts' reports to guide their investment decisions. The evidence in the accounting and finance literature implies that analysts significantly alter market expectations (e.g., Stickel 1995, Womack 1996, Kothari 2001), and analysts deemed particularly successful in their endeavor quickly earn "superstar"-status via high profile awards, press coverage and lucrative compensation packages. Such accolades are predicated on the assumption that a large portion of the analyst's performance is person-specific and portable, i.e., independent of the brokerage employing the analyst in question.

These results also have implications for other knowledge-based production industries.[5] Physical access and geographical proximity have traditionally been important for knowledge-based production. A decrease in the cost of communication make information production cheaper even at a distance, and impose a cost on the power that a firm has to control the knowledge it has accumulated. If a firm is not able to contain information spillovers, this may drive firms to outsource information production outside the boundaries of the firm thus eliminating the advantages of spillovers due to task complementarities.

The rest of the paper is organized as follows. Section 2 presents the data. Section 3 describes the empirical strategy. Section 4 presents the main result on overlap in coverage. Section 4 also provides a rationale for the degrees and limitations of information spillovers including the impact of intuitional factors, geographical location of analysts, information content of mergers, aggregate information environment, coordination costs, team size and degree of analyst specialization. Section 5 describes some identification concerns and Section 6 concludes.

[5] For example, Kim, Morse, and Zingales (2009) examine research productivity in elite universities and question whether these universities have lost their competitive edge.

2. Data

Our investigation examines financial analyst productivity around real firm mergers. We identify real firm mergers by relying on information from the SDC Mergers and Acquisition database. We filter those mergers in which there was a publicly traded acquirer and target using CRSP. We identify target firms in the CRSP database via the delisting file and by whether a security is marked by a first-digit delisting code of 2 or 3. The delisting file provides us with the PERMNO of the disappearing target firm as well as the PERMNO of the acquirer firm, which overwrites the PERMNO of the disappearing firm.

We match these PERMNOs for the acquirer and target to the Institutional Brokers Estimates System (IBES) database. We focus on quarterly earnings forecasts, and include only those forecasts made within 90 days of the earnings announcement report date. For each analyst-stock pair, we measure productivity using the scaled forecast error. For each analyst *i* following the acquirer affected by the merger *m*, we compute the scaled forecast error (FE) for quarterly earnings *t* announced in the two-year window around the effective date of the merger. Scaled forecast error (FE) is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst *i*'s most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement:

$$FE_{i,m,t} = \left| \frac{EPS_{m,t} - forecast_i(EPS_{m,t})}{P_{m,t}} \right| \tag{1}$$

Throughout, we present the scaled forecast error (FE) as a percentage. On average, the scaled forecast error is 0.172% in the real firm merger sample. In our main analysis, we focus on analysts that cover the acquirer and provide coverage both pre- and post merger. Additionally, for each analyst we collect time variant characteristics such as firm-specific experience, stock coverage, sector coverage, and location.

The resulting sample includes 4,316 analysts working at 360 brokerages covering 2,558 acquirers in real firm mergers (20,109 analyst-stock pairs). However, since we are interested in studying the treatment effect of organization of information on analyst productivity within brokerage-analyst, we restrict the data to broker-analysts for which we observe multiple acquisition coverage and variation in the overlap in coverage of the target. To understand the degree of overlap, we classify each analyst as Type 1, Type 2, or Type 3. Consider the setting of *Analyst 1* working at *Broker A* following the acquirer in three separate mergers, and that there is second analyst, *Analyst 2*, working at the same broker. Then, the coverage prior to the merger is as follows:

Broker A: *Analyst 1* covers *Acquirer* (*Analyst 1* ≡ Type 1)

Broke A: *Analyst 1* covers *Acquirer*, *Analyst 2* covers *Target* (*Analyst 1* ≡ Type 2)

Broker A: *Analyst 1* covers *Acquirer* and *Target* (*Analyst 1* ≡ Type 3)

Type 1 analysts exhibit no overlap, while both Type 2 and Type 3 analysts exhibit some specific overlap. Thus, mergers for which the analyst is Type 1 provide a control group for those when they are Type 2 or 3. Further, Type 2 analysts exhibit overlap at the brokerage level, while Type 3 analysts exhibit overlap at the brokerage *and* individual level. Thus, if information spillovers are valuable in the context of forecast accuracy for the newly merged firm, then both Type 2 and 3 analysts should be at a distinct advantage compared with the control group Type 1 analyst. Further, Type 3 analysts should provide a useful benchmark for the potential of information sharing.

Our final sample consists of 2,394 analysts working at 215 brokerages covering 2,403 acquirers in real firm mergers (15,939 analyst-stock pairs). In Table 1 we provide descriptive statistics for real firm mergers. On average, acquirer firms are approximately six times larger than target firms, with around seventy percent of mergers being related mergers within the same industrial sector. Given that we focus on analyst forecasts and the information environment, it is particularly important to consider differences in analyst following across acquirer and target. The number of analysts following the acquirer is approximately three times that of the target. The lower coverage of the target might result in lower levels of information for the target and/or bias in forecast error (see Hong and Kacperczyk (2010) for the effects of competition on bias in the analyst setting). In later tests, we examine whether the extent of target coverage impacts the role for information sharing.

In Table 2 we present descriptive statistics for the financial analysts included in our final sample. Type 1 analysts are the most common type (69%), followed by Type 3 (22%), and Type 2 (9%) analysts. The scaled forecast error in the period prior to the merger is comparable across those analysts that feature and overlap in coverage in those that do not. The difference of 0.005 is economically small (3% of the scaled forecast error) and statistically insignificant. Examining analyst characteristics, Type 3 analysts have slightly greater experience, and tend to cover smaller acquirers that make larger acquisitions. In comparison, Type 2 analysts are more likely follow larger acquirers. Both Type 2 and Type 3 analysts tend to cover larger acquisitions than Type 1 analysts. Type 3 analysts exhibit greater scope in terms of stock and sector coverage, while Type 2 analysts tend to be more specialized.

Of course, one should be careful when comparing across analyst types. By design, we focus on analysts that cover both mergers where there is an overlap and those where there is no overlap. Therefore, comparisons across columns (2) and (3) in Table 2 are comparisons across the same groups of analyst, but for different mergers. In contrast, comparisons within the overlap observations across columns (4) and (5) may involve a comparison across two groups of analysts. In formal conditional tests, we ensure that our results are not driven by such differences.

3. Empirical Design

Our identification strategy relies in examining the change in forecast error around a merger event within brokerage-analyst. As pointed out before, estimating all our results in a within broker-analyst framework ensures that the results are not driven by non-random changes in brokerage houses (i.e., selection effects)[6]

The real firm mergers in which there is overlap in coverage of the target within the brokerage organization provide the treatment group, while those for which there is no overlap provide the control group. To the extent that examining differences in the treatment and control group, within brokerage-analyst, mitigate selection concerns because our inferences our made for the same analyst working for the

[6] Our approach is equivalent to a within analyst estimation if an analyst does not change her brokerage house.

same brokerage any result we find can be attributed the treatment effect of variation in information environment or spillovers. Of course, the stocks that an analyst follows are not randomly allocated. However, so long as real mergers are unrelated to whether the analyst's own brokerage covers the target then it is plausible that the variation in target coverage and spillovers is random. Indeed, this experiment would seem to satisfy the exclusion restriction that the change in forecast error of the treatment versus the control sample across the merger date is not due to any factor other than the real firm merger leading to variation in coverage of the target by the brokerage.

Our empirical methodology requires that we examine the change in forecast error for each analyst stock around the merger event. Thus, we need to observe analysts that follow multiple acquirer firms, analysts for whom there is variation in coverage of the target by peers within the brokerage, and analysts that follow the acquirer prior to and post merger. We focus on those analysts that follow the acquirer (as opposed to those that follow the target) because it provides a baseline forecast with which to compare the post-merger forecast against. To examine the difference in forecast error around the merger we choose a representative window of two years either side of the merger event. For each analyst-stock pair we take the average of the forecast error in each pre- and post-event period, which leaves us with a two observations for each analyst-stock pair – one prior to the merger event and one post the merger event.

The representative window is chosen for a few reasons. First, most analysts will typically issue at least one forecast within a twelve-month window. However, this means that the forecast might be up to twelve months from the merger. Consequently, choosing a short window, as is typically preferred in event studies, might result in losing observations because analysts may not issue forecasts on the same date or with the same frequency. Further, averaging over a longer window helps alleviate the concern that compounding events might contaminate a single point estimate far from the event.

In the empirical analysis, we measure the effects of information spillovers on productivity by estimating the change in forecast error, $\Delta FE_{m,i,j,t} = \overline{FE_{m,\imath,\jmath,post}} - \overline{FE_{m,,\imath,\jmath,pre}}$, around the merger for each analyst-stock pair on *Overlap*, which is a dummy variable equal to one if there is an overlap in coverage for that particular analyst-stock. The main specification is of the following form:

$$\Delta FE_{m,i,j,t} = \alpha_{i,j} + \alpha_t + \beta_1 Overlap_{m,i,j,t} + \varepsilon_{m,i,j,t}, \qquad (2)$$

where $\Delta FE_{m,i,j,t}$ is the change in absolute forecast error of analyst i (employed by brokerage j) covering the acquirer firm m, where the merger occurs in year t; $\alpha_{i,j}$ and α_t are broker-analyst and year-fixed effects; and $Overlap_{m,i,j,t}$ equals one if there is an overlap in coverage for merger m at brokerage j where analyst i follows the acquirer. The broker-analyst fixed effects ensure that we are making comparisons within an organization-individual match, which should absorb selection effects. To control for time-series variation in the aggregate information environment that might affect the change in forecast error, we include calendar year dummies. Standard errors are computed after allowing for correlations across observations in a given broker-analyst-level.

The estimation in equation (2) is equivalent to a difference-in-differences (DiD) estimator in which we estimate the DiD for each broker-analyst, by comparing the treatment group observations with the control group observations, and then average across all broker-analysts. The estimation in equation (2) is preferred because it allows us to examine heterogeneity in treatment effects. One such heterogeneity is the degree of overlap. At one end of the spectrum, the overlap is with the individual, *i.e.*, the analyst covers the acquirer and target. In this instance, the analyst should be in the best possible position – from an information perspective – to follow the merged firm. Next, an overlap may exist where the peer analyst covering the target sits at the same geographical location and/or focuses on the same industry. Lastly, we have an overlap at the brokerage level but analysts may be geographically distant, and focus on different industries.

A common concern in DiD estimation is that the treatment and control groups may be significantly different from each other and, therefore, and hence the partial effect may additionally capture the differences in the characteristics of the different groups. In our setting this is unlikely because the treatment and control groups are the same group of broker-analysts and inference is made within broker-analysts. Thus, our results are robust to concerns such as the treatment group is concentrated in certain types of brokerages that may be resource-rich or contains particular types of analyst. However, two sources of variation might still plague our results. First, the mergers for which the analysts are in the treatment versus in the control might differ. There is no reason to believe this to be case because it is unlikely that brokerages choose to follow stocks based on mergers that are *yet* to happen. Nonetheless, in later tests we examine merger heterogeneity effects and also show that results are robust to absorbing the cross-sectional merger-specific change in forecast error. Second, the calendar year effects mitigate any concerns relating to not only the aggregate information environment, but also the time-series variation in forecast accuracy and any time-series variation in merger waves or merger types that may impact the change in forecast error around mergers.

Before proceeding to our results, a few facets of our general empirical approach are noteworthy. We study the treatment effect of organization of information on individual productivity. Thus we can exploit plausibly random variation in the organization of information within the same brokerage to understand the causal effects of information spillovers on productivity. This allows us to absorb selection effects in a manner that would not be possible if we were to study the effect of organization characteristics on individual productivity, using a fixed effects method, similar to Bertrand and Schoar (2003), for example. The fixed-effects method also makes it challenging to infer the exact mechanisms through which analyst- and brokerage effects manifest themselves. More crucially, the fixed-effects method draws its power from analyzing changes in performance as an analyst moves from one broker firm to another. Most job transfers cannot be thought of as independent of the analyst-person-specific performance component and, instead, represent a promotion or demotion. Disentangling the treatment effects and selection effects using job transfers is thus difficult, if not impossible, to do in our setting.

Second, it is worth emphasizing the importance of our specification. Employing broker-analyst fixed effects allows us to examine variation within broker-analyst while holding selection effects constant. In contrast, including no fixed effects would estimate results that include both selection and treatment effects. Including analyst fixed effects would offer similar inference as for brokerage-analyst fixed effects but selection effects would influence results because we would also be making comparisons across brokerages. Lastly, including brokerage fixed effects would hold the organizational capital constant but comparison would be made across analysts. To the extent that two analysts working at the same brokerage are interchangeable this would be fine. However, it is likely that analysts exhibit different skills, are allocated to very different portfolios of stocks, and might also be more or less amenable to information transfer.

The final note concerns our use of earnings forecast error as a measure of analyst performance. Earnings forecasts represent only one of two primary quantifiable outputs that analysts produce. The second output is the analyst's overall recommendation on whether the stock should be bought, held or sold. We focus on earnings forecasts as they can be easily evaluated against the actual earnings announced; stock recommendations lack such a clear objective benchmark.

4. Main Results

4.1 Analyst Performance and Overlap in Coverage

We begin our analysis with an assessment of how the forecast error changes after a real firm merger. We first examine unconditional changes in forecast error. The descriptive statistics presented in Table 2 shows that scaled forecast errors, on average, increase by 0.058 for the newly merged firm relative to the acquirer firm (prior to the merger), which is economically meaningful (the change is equivalent to 33% of the average scaled forecast error in the period pre-merger) and statistically significant from zero at the 1%-level. This increase in forecast error is consistent with the notion that the earnings of the newly merged firm, at least initially, are more uncertain than those for the acquirer firm considered by itself.

Comparing the change in forecast error across types, we observe that the change in forecast error is smaller in observations for which there is an overlap (column 3); the difference in the change in forecast error between those observations where there is no overlap (Type 1 analysts) and those where there is an overlap (Type 2 or Type 3 analysts) is -0.030 (statistically significant from zero at the 1%-level). Finally, we observe that forecast error increases substantially less for analysts of Type 3; the difference in change in forecast error between Type-3- and Type-1 analysts is -0.048 and statistically significant from zero at the 1%-level. Overall, these patterns are consistent with higher acquirer analyst productivity when there is an overlap in coverage such that the analyst has access to research on the target firm.

We examine the change in forecast error for acquirer analysts more formally in Table 3 using specification (2). As a reminder, we are interested in whether the information environment offered by the organization (the treatment) affects individual performance. To ensure that any results we find are not due to selection we estimate the effect of variation in the information environment on changes in forecast error holding the broker-analyst relation constant. To build intuition for our empirical strategy, in column (1) of Table 3, we first estimate specification (2) with year fixed effects only. We find that the change in forecast error is lower by -0.054 (and statistically significant at the 1%-level) for analysts that exhibit an overlap compared with the counterfactual of no overlap. This estimation is similar to the unconditional evidence presented in Table 2 except that we absorb any time-varying aggregate effects on the change in forecast error. Importantly, this means that we make comparisons both across analysts and brokerages. Clearly, this estimation is plagued by selection. We do not observe the matching process of analysts to brokers, nor do we observe analyst skill or organizational capital.

Next, in column (2) we estimate specification (2) with brokerage fixed effects. We find that the change in forecast error is lower by -0.057 (and statistically significant at the 1%-level) for analysts that exhibit an overlap. The inclusion of brokerage fixed effects goes some way to address selection. We absorb (time-invariant) organizational capital and to the extent that two analysts working at the same brokerage have the same selection effects, *i.e.*, they are interchangeable, we also mitigate concerns about the broker-analyst match. However, while two analysts working at the same broker might be similar, it is unlikely they have identical attributes. This is problematic if the variation in analyst ability results in variation in selection of stock coverage, for example.

To fully mitigate these selection effects, we turn to the specification proposed in Section 2 using a within brokerage-analyst framework. We estimate specification (2) with broker-analyst fixed effects in column (3). Thus, we compare changes in forecast error across variation in overlap for the same analyst working at the same brokerage. Since selection effects should be common within a broker-analyst pair, our strategy absorbs selection effects and any results can be attributed to treatment effects. We find that the change in forecast error is lower by -0.042 (and statistically significant at the 1%-level) for analysts that exhibit an overlap compared with the counterfactual of no overlap. This effect is large: compared to the average change in forecast error of 0.067 for no overlap presented in Table 2, the result in column (3) implies that information spillovers in the form of overlap in coverage of the target improve performance by around 60%.

The results presented in column (3) estimate effects within broker-analyst, but compare the change in forecast error for two or more mergers at different points in time. Our identification assumption relies on the forecast error being comparable across mergers for the same broker-analyst pair. Of course, not all mergers are equal. Consequently, one final concern is that time-varying differences in the portfolio of stocks that the analyst follows might both explain the overlap in coverage and the relatively better performance. Since the overlap in coverage is exogenous to the analyst there is no systematic reason to believe that changes in analyst characteristics for the same analyst should explain our results. Nonetheless, in column (4) we include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, the size of the analyst's team, and sector-year fixed effects to mitigate such a concern. The stock-specific experience of the analyst measures the time that the analyst has been following the acquirer. Our results show that mergers create uncertainty in forecasts; potentially analysts with more experience of the acquirer might be better able to deal with this uncertainty. The number of stocks the analyst follows and the number of sectors the analyst follows attempt to measure the portfolio of stocks the analyst covers, while the size of the analyst's team attempts to measure organizational design. Finally, sector-year fixed effects allow us to control for time varying sector effects on forecast error that might affect an analyst if they follow more than a single sector. Once again, the results show that information spillovers positively affect performance in our setting. The change in forecast error is lower by -0.038 (and statistically significant at the 1%-level) for analysts that exhibit an overlap compared with the counterfactual of no overlap.

We drill further into these results in column (5) to shed light on the nature of the overlap. As we described in Sections 2 and 3, the overlap in target coverage may take two forms. In the first case (the Type 2 analyst) the overlap exists because a peer analyst working at the same brokerage covers the target firm. Alternatively, it could simply be that the acquirer analyst also follows the target firm (the Type 3 analyst). We separate out the effects of overlap into Type 2 and Type 3 analysts (Type 1 analysts with no overlap remain the counterfactual). The results show that both types of overlap matter for performance. The coefficient on *Overlap – Type 2* is -0.023 (and statistically significant at the 10%-level), while the coefficient on *Overlap – Type 3* is -0.045 (and statistically significant at the 1%-level), and the difference between *Overlap – Type 2* and *Overlap – Type 3* is significant at the 10%-level. Perhaps unsurprisingly, the merger least affects forecast error when the analyst covers both the acquirer and target. However, the result for Type 2 analysts reveals that information spillovers within the same organization across analysts also affect individual performance.

Overall, these results are consistent with information sharing and spillovers being an important factor in individual-level productivity. In particular, analyst performance is greater for mergers in which the analyst can share information on the target with a peer than for mergers where the same analyst has no such peer. However, the results also show that information sharing by two individuals underperforms the case in which a single individual collects information.

4.2 Information Spillovers

The degree to which information spillovers exist within an organization might depend on both organizational and human capital. We next investigate the nature of the information spillovers in our setting by examining how the within broker-analyst treatment effect (i.e., Type 2 vs. Type 1 performance) varies by factors that might shape the information environment.

4.2.1 Institutional Effects

We start by examining if information spillovers are greater in organizations that are likely wealthier in terms of information and/or technology that enable easier communication between employees. For example, larger brokerages may have greater organizational capital or are better able to justify and afford technology that reduces communication costs. Equally, it may be that analysts working for larger brokerages may be more, or less, likely to be Type 2 or Type 3 analysts.

To examine how institutional details might affect performance, we measure the size of brokerage using the number of stocks that the brokerage covers, the number of analysts that the brokerage employs, and the number of sectors that the brokerage covers. On average, brokerages employ 49 analysts covering 483 stocks across 9 (of the 10) GICS sectors. Comparing across analyst types, analysts for which there is an overlap in coverage work for larger brokerages. Within those with overlap in coverage, Type 2 analysts tend to work for larger brokerages (the average number of analysts is 58 and the average number of stocks covered is 562), while Type 3 analysts work for slightly smaller brokerages (the average number of analysts is 51 and the average number of stocks covered is 504).

Organizational capital, and the selection of analysts into brokerages with different organizational capital, undoubtedly affects performance. We examine unconditional changes in forecast error across institutional size and find that larger brokerages are typically associated with worse performance. For each of the number of stocks that the brokerage covers, the number of analysts that the brokerage employs, and the number of sectors that the brokerage covers, we classify the brokerage as *Large* if the brokerage value is above median. Examining unconditional changes in forecast error across institutional size we find that larger brokerages are typically associated with worse performance. For example, the change in forecast error is 0.050 (0.066) for small (large) brokerages, based on the number of analysts employed by the analyst, with the difference significant at the 5%-level. This is reassuring, as analysts for whom there is an overlap tend to work for larger brokerages. Hence this unconditional difference suggests that comparisons of within-analyst effects across institutions do not explain the results presented in Table 3.

We present the results for organizational capital in Table 4. In columns (1) – (3) we present results that explore if brokerage size impacts performance in a conditional setting using specification (2). In all three measures of organizational capital – number of stocks, analysts, or sectors – we find that our previous results hold. Both Type 2 and Type 3 analysts outperform Type 1 analysts. However, we also find that the performance of Type 2 analysts increases with organizational capital. This result implies that the value of being a Type 2 analyst, over and above a Type 1 analyst, increases in the size of brokerage consistent with these types of brokerage having lower communication costs. Unsurprisingly, we find no such effect for Type 3 analysts for whom there are zero communication costs.

Lastly, we examine brokerages that are located in New York. New York brokerages are, on average, larger in terms of all three of our measures. They are also arguably more prestigious, which might be correlated with better organizational capital. Consequently, based on the results in columns (1) – (3), we should expect Type 2 analyst to fare better in brokerages in New York. The results in column (4) once again show that Type 2 analysts perform better on average, but also their performance differentially increases with the organizational capital of the brokerage

4.2.2 Location and Limits to Information Sharing

The ability to transfer information between agents has implications for spillovers in our setting. For example, soft or subjective information on firms, collected by analysts to gain strategic advantage, will be more costly to transfer to a second analyst than will hard or objective information. Consequently, one might expect the organizational design of the brokerage, such as location, distance between analysts, and team size, to affect the effectiveness of information spillovers given the subjective nature of the information being communicated.

A few recent papers examine if location clustering affects stock investment decisions. Ahern (2014) finds that insider trading is more prominent among traders that cluster by location and that the profitably of trades decreases with distance. Hong, Kubik, and Stein (2005) find that mutual fund managers are more likely to trade stocks if managers in the same locale trade the same stock. Brown, Ivković, Smith, and Weisbenner (2008) show that investors share portfolio choice decisions with peers within the local community.

In Table 5 we explore how geographical proximity affects information spillovers in our setting. We identify when a brokerage has a single location and also when a Type 2 analyst covering the acquirer and her peer covering the target share the same location. We find that 7% of Type 2 analysts work for brokers with a single location, while 32% of Type 2 analysts share a location with their peer that covers the target firm. In column (1) we present the results for Type 2 analysts working in a single location brokerage. The estimation splits overlap in coverage into three components, Type 2 analysts, Type 2 analysts working at a single brokerage location, and Type 3 analysts, with Type 1 analysts the counterfactual for each analyst type.[7] We find negative and significant coefficients for both *Overlap - Type 2* and *Overlap - Type 2 × Location*, consistent with information spillovers being greater when the two analysts share a location. In column (2), we examine if analysts that share the same location within a brokerage that spans multiple locations are also at an informational advantage compared to geographically distant analysts. We find The coefficient for *Overlap - Type 2* is negative but not significant (the p-value is 0.12), while the coefficient for *Overlap - Type 2 × Location* is negative and coefficient, once again consistent with information spillovers being greater when the two analysts share a location.

The results presented in columns (1) and (2) of Table 5 provide evidence that location clustering is an important factor in explaining information spillovers in financial markets. While information spillovers improve productivity, the analyst performs better if information spillovers originate from peers in the same locale.

Next, we turn attention to how team size affects information spillovers. Becker and Murphy (1992) argue that, while returns to the time spent on tasks are usually greater to workers who specialize

[7] In column (1) of Table 5, whether the brokerage has a single or multiple locations does not vary within broker-analyst. Thus, the comparison of *Overlap - Type 2* with *Overlap - Type 2 × Location* compares treatment effects for different analysts. However, in column (2), the comparison of *Overlap - Type 2* with *Overlap - Type 2 × Location* is within analyst.

on a narrower range of skills, there is a trade-off to such specialization. The cost of such specialization is coordination across workers and these costs are increasing with team size. In the context of financial analysts, who are specialized in terms of the stock they cover, coordination across a Type 2 analyst and her peer may be more difficult if they are part of a larger team.

Financial analysts typically work in teams. Teams may involve multiple analysts working across similar stocks that require some common expertise, or multiple analysts covering the same stock. Unfortunately, we do not directly observe team structure at brokerages. Instead we define a team as the number of analysts working within a GICS industrial sector. This approach seems reasonable given that analysts typically work for an "industrial" group or team. For example, Martin Romm followed Coca Cola at CSFB and worked in "Beverages," while Gerard Rijk followed Heineken at ING and also worked in "Beverages." The mean (median) team size in our sample is 14 (12) analysts, with a standard deviation of 11 analysts.

In column (3) of Table 5 we present evidence on team size. We estimate the difference in forecast error on *Overlap - Type 2*, *Overlap - Type 3*, *Team Size* and *Overlap - Type 2 × Team Size*, where Team Size is the natural logarithm of the number of members in the analyst's team. As with our main results we find that information spillovers for Type 2 analysts improve performance. However, the coefficient for *Overlap - Type 2 × Team Size* is positive (0.024) and statistically significant (at the 10%-level), consistent with larger team size decreasing the benefits of information spillovers. Using the coefficients of -0.030 and 0.024 for *Overlap - Type 2* and *Overlap - Type 2 × Team Size* respectively, a back of the envelope calculation reveals that information spillovers cease to be performance enhancing for a one-standard deviation increase in team size, or equivalent a team size of around twenty five.[8] Finally, in column (4) we examine the effects of team size and brokerage size, measured as the number of analysts, together. Results in Table 4 on brokerage size showed that information spillovers are greater in larger organizations. If larger organizations tend to have larger teams, then the results in column (3) seem at

[8] The mean (standard deviation) for team size if 14 (11) analysts, while the standard deviation of ln(team size) is 0.96. Hence a one-standard deviation in team size almost eliminates the effect of spillovers based on coefficients of -0.030 and 0.024 for *Overlap - Type 2* and *Overlap - Type 2 × Team Size* respectively.

odds with this result. We include both *Team Size* and *No. of Analysts* in the same estimation and find that both results stand. Our interpretation is that the *No. of analysts* captures organizational capital while *Team Size* captures the coordination problems highlighted by Becker and Murphy (1992).

Overall, the results in this section shed light on the limitations to information sharing. Guided by theory, we show that greater distance and team size increase communication and coordination costs between analysts, which in turn limit the degree of information sharing. The results have wider implications for individual productivity in knowledge-intensive industries and are consistent with recent work examining individual decision-making on financial investments.

4.2.3 All-Star Analysts

In knowledge-based industries like finance there is often the assumption that top-performing individuals (i.e., stars) and their talent are highly portable. Therefore, one should expect stars to be able to apply their skills across not only multiple organizations but also multiple tasks within an organization. The presence of star analysts has a few implications for our study. First, stars are more productive and thus may be better able to deal with uncertainty or a combination of tasks as we observe in a real merger. Second, stars have greater visibility, which may in turn mean they have more power within the firm and therefore demand a greater share of resources, including information, within the organization.[9] Third, if Type 2 and Type 3 analysts are systematically stars, then our prior results might be explained by the presence of stars.

We identify star analysts as those analysts who were named to the *Institutional Investor*'s All-America Research Team in a given year, commonly known as *All-Star Analysts*. Although many rankings of individual analysts are published each year, the choice of *Institutional Investor*'s All-America Research Team is appropriate for our analysis. Hong, Kubik, and Solomon (2000) note that sell-side analysts generally aspire to be *Institutional Investor* All-Americans. Dunbar (2000) and Krigman, Shaw, and Womack (2001), and Clarke et. al. (2007) show that firms value All-Star analysts when selecting equity

[9] Power, in this context, refers to the analyst's ability to create a critical resource that she controls – her human capital. See Rajan and Zingales (1998) for an exposition of power in the theory of the firm and access to information as a critical resource.

issuance underwriting and M&A advisors. Leone and Wu (2007) document that these All-Star analysts have better earnings forecast accuracy, better stock recommendation returns, and smaller optimism bias than their non-star counterparts.[10]

We start by examining the composition of All-Star analysts. On average, eleven percent of analysts are All-Stars. Using a similar sample, Groysberg, Lee, and Nanda (2008) find that star tenure is on average 6.6 years. Consequently, one expects to observe both cross-sectional and within-analyst variation in All-Star status. Examining All-Star status by analyst type, we find that eleven percent Type 2 analysts are All-Stars, while thirteen percent of Type 3 analysts are All-Stars. Unconditionally, at least, this implies that Type 2 analyst effects are not a determinant of All-Star status.

In Table 6, we identify Type 2 analysts that are All-Star analysts, whether the peers that cover the target alongside the Type 2 analyst are All-Stars (*Peer is All-Star*), and the Type 3 analysts that are also All-Stars. In column (1), we show that All-Star status has no effect on our earlier results. Additionally, All-Star status has no effect on the performance of an analyst, which implies that the talent the analyst is rewarded for is innate. In column (2) we examine if being an All-Star analyst while being a Type 2 or Type 3 analyst is advantageous. The coefficient of -0.059 on *Overlap - Type 2 × All-Star* indicates that All-Star status increases performance for Type 2 analysts. In fact, there is no difference in performance between when the analyst is an All-Star Type 2 analyst and when she is a Type 3 analyst. This result is consistent with stars both having higher power and productivity. Stars may be better able to placed to collect information from peers and also more able to process such information.

In column (3) of Table 6, we investigate if having an All-Star peer covering the target impacts forecast error for Type 2 analysts. While the coefficient for *Overlap - Type 2: Peer is All-Star* is negative, it is insignificant. Thus, a star's talent does not necessarily spillover into peers' productivity. The results

[10] Leone and Wu (2002) discuss the selection procedure for the all-American team. To summarize the procedure, selection to the All-American team is based on survey data. Institutional Investor sends out a questionnaire to the directors of research and chief investment officers of money management institutions and also to other sell-side analysts. They rank each analyst based on the following six dimensions: accessibility and responsiveness, earnings estimates, useful & timely calls, stock selection, industry knowledge, and written reports. Scores for each analyst are calculated by taking the number of votes awarded by each survey respondent and weighting them by the size of the respondent's firm. The results are published each year in the October issue of the magazine.

in Table 6 show that stars are better able to capture information spillovers, consistent with stars having both higher power in the firm or higher productivity.

4.2.4 Heterogeneity in the Information Content of Mergers

The extent to which information spillovers are valuable will depend on the increase in uncertainty in earnings for the merged firm. In this section we explore how the information content of mergers impact analyst productivity by focusing on two key characteristics of a merger – scope, which measures if the merger is related or diversifying, and size, which measures the size of the target relative to the acquirer. Mergers that result in relatively small changes in firm scope might prove less challenging because an analyst has expertise in this area and also likely covers a group of similar firms within her portfolio. Additionally, communication costs between peers may be lower for related mergers because forecast inputs, models, and analysis are more likely to be similar. Smaller acquisitions are easier to follow simply because the merger affects less of the acquirer. This is especially true for Type 1 analysts who have no access to target information.

In Table 7 we examine how the information content of the merger affects information spillover related productivity. We start with the scope of the merger by identifying related mergers as those for which the acquirer and target share an industrial sector. In column (1) we present cross-sectional evidence, controlling for analyst characteristics and year fixed effects, to give intuition for how related mergers affect the change in forecast error. The variable *information* is a dummy variable equal to one for related mergers. Comparing the coefficient for *Information* of -0.026 with the aggregate change in forecast error in Table 2 implies that the forecast error is approximately a third lower for related mergers than for diversifying mergers. In column (2), we estimate the effects of merger scope on performance including broker-analyst fixed effects. Once again, analyst productivity is less adversely affected by related mergers, even controlling for organizational, individual, and selection effects.

Next, in column (3) of Table 7 we test if our main results on information spillovers are robust to controlling for merger scope. The analyst exhibits a smaller decline in performance for related mergers, but both Type 2 and Type 3 analysts outperform Type 1 analysts. In column (4), we examine if spillover effects vary with firm scope. We interact the dummy variable *information* with both *Overlap - Type 2 and Overlap - Type 3*. As before, productivity is less affected for related mergers, and information spillovers increase performance. However, the negative coefficient on *Overlap - Type 2* × *Information* implies that the value of information spillovers is increasing for related mergers, consistent with communication costs being lower for related mergers. On the other hand, the positive coefficient on *Overlap - Type 3* × *Information* suggests that the information advantage of being a Type 3 analyst is lower for mergers where the acquirer and target are more similar.

In the remainder of Table 7 we switch attention to the size of the acquisition. We measure *Target as % of Merged Firm* (the variable *Information* in columns (5) – (8)) as the ratio of the target's market equity to the sum of the combined firm's market equity, all measured in the quarter prior to the transaction. The average merger involves targets that are approximately one-sixth the size of the acquirer and less than five percent of transactions involve targets larger than the acquirer. In column (5) we show evidence that, on average, target size does not affect analyst performance around a merger. At first glance this is surprising. However, there are likely different forces at play that can explain this result. While smaller mergers are less disruptive to forecasts, smaller targets are less likely to be followed by analysts or covered in the financial media. Therefore less may be known about these targets in aggregate. Furthermore, larger acquisitions may result in less integration in the short to mid-term which means merged earnings are simply a weighted average of the target's and acquirer's earnings. We find similar results when examining the effect of merger size within broker-analyst in column (6).

In columns (7) and (8) of Table 7, we examine if spillover effects vary with the size of the merger. The results in column (7) illustrate that the main results are unchanged once we control for size. In column (8), we interact *Information* with *Overlap - Type 2* and *Overlap - Type 3*. The negative coefficient on *Overlap - Type 2* × *Information* implies that the value of information spillovers is increasing for larger mergers, relative to those instances for which there are no information spillovers.

This is wholly consistent with future earnings in larger mergers being more uncertain, and information spillovers within the firm being valuable in eliminating some of the uncertainty.

Overall, we find that information sharing by peers is more valuable when the information is less costly to transmit across agents or when the benefits of information sharing are greater. These results both help us better understand the role of information spillovers and provide support for our main results.

4.2.5 The Aggregate Information Environment

The information environment facing the analyst is a combination of the internal information environment set by the organizational structure – the focus of this study – and the aggregate information environment that is external to the organization.[11] In the context of our setting, the aggregate information environment might capture the number of analysts following the acquirer and target firms. The information set for the target firm will be richer where a greater number of analysts cover the target firm prior to the merger, which in turn might reduce uncertainty in earnings forecasts for the merged firm for all analysts. In this section, we explore how aggregate information affects information spillover effects.

In Table 8 we examine how analyst following impacts performance around mergers. We measure the number of analysts following each of the acquirer and target in the two years prior to the merger. On average, there are 16 analysts covering the acquirer, while there are 6 analysts covering the target. The variation in coverage is not surprising given the relative sizes of the acquirer and target. In column (1), we examine whether the number of analysts following the target impacts performance in the cross-section of analysts. The coefficient for *Target Analyst Coverage* of -0.003 shows that the uncertainty in earnings forecasts is lower where there is a richer set of aggregate information for the target. A one-standard deviation increase in analyst following for the target decreases forecast error by 0.020, or approximately one-third of the average change in forecast error. In column (2) we confirm that these results are not an artifact of analyst composition by finding a similar result when including brokerage-analyst fixed effects.

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[11] A few studies have examined how the aggregate information environment affects the demand for information production by analysts. For example, Lehavy, Li, and Merkley (2011) show that analyst following is greater for firms with less readable annual reports.

Next, in column (3), we examine if acquirer analyst coverage affects performance. Since each of the analysts we track around the merger follow the acquirer prior to the merger and already are exposed to the aggregate information set for the acquirer it is unclear that aggregate analyst coverage for the acquirer should impact performance. However, it is possible that greater aggregate coverage reduces uncertainty around earnings post merger, or that there is a greater potential for learning from rival analysts. We estimate performance on both *Target Analyst Coverage* and *Acquirer Analyst Coverage* and find no effect for acquirer coverage, while target coverage effects are similar as for column (2). The results imply that, while target coverage increases analyst performance in covering the merged firm, acquirer coverage has no effect.

In columns (4) and (5) we explore how aggregate target coverage affects information spillovers. There is significant variation in aggregate target coverage by analyst type. For Type 1 analysts there are 4 analysts covering the target on average, while for Type 2 and Type 3 analysts there are 7 and 13 analysts respectively. In light of this variation, and the results in columns (1) – (3), it is important to examine if the spillover effects are robust to including aggregate target analyst effects. In column (4) we show that this is the case. However, in column (5), where we examine how spillover effects vary with target analyst coverage by including interactions of analyst type with aggregate target coverage, we find that the coefficients for both *Overlap - Type 2* and *Overlap - Type 2 × Target Analyst Coverage* are negative but insignificant. Switching attention to the Type 3 analysts, we find a negative coefficient for *Overlap - Type 3* and a positive coefficient for *Overlap - Type 3 × Target Analyst Coverage*. Taken together, this implies that the information advantage for a Type 3 analyst is greatest when there is weaker aggregate information, and the advantage over a Type 1 analyst shrinks as aggregate information environment strengthens. Combined, the results in columns (4) and (5) show that information spillovers are valuable for individual performance, but also that spillovers may also originate external to the firm.

4.5 Specialization

Since Adam Smith, specialization is typically associated with higher returns to labor. Financial analysts obviously share similar skills but specialization in specific stocks or sectors gives them comparative advantage in forecasting and valuation for the stocks they follow. In this section we examine how specialization affects productivity of analysts in general and also the role for information spillovers.

In the context of financial analysts, specialization implies that the analysts develop a narrower range of expertise and cover stocks that are similar in terms of the fundamental analysis required. Specialization might result in comparative advantage because the analyst has greater incentives to become an expert in the sector, including following competitive trends such as M&A, or because they collect and process related information from different stocks that when combined result in more accurate analysis for all stocks in their portfolio. With this in mind, we measure specialization as the natural logarithm of the number of firms the analyst follows per sector and interpret a greater number as greater specialization.[12] On average, the analyst covers 10.6 stocks per sector with the standard deviation of 7.0 stocks.

In Table 9 we formally examine how specialization affects productivity. In column (1) we present cross-sectional evidence and find that more specialized analysts exhibit smaller declines in forecast accuracy around mergers. The coefficient of -0.023 for *Specialization* implies that a one standard deviation increase in specialization is associated with decrease in the change forecast error of -0.04, or around two-thirds of the average change in forecast error. In column (2) we examine the effects of specialization within analyst and find similar results.

Next, we examine how specialization affects information spillovers. A natural concern when comparing the results in columns (1) and (2) with our main results on information spillovers is that if Type 2 and Type 3 analysts are more specialized this might explain their superior performance around mergers. In column (3), we find that spillover and specialization effects are additive and that specialization does not explain the performance associated with Type 2 and Type 3 analysts. Finally, in

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[12] We find similar results if we use alternate measures for specialization such as 1/No. of Sectors, for example. In the estimations testing the effects of specialization we drop the number of sectors from our control group.

column (4) we explore if information spillovers are stronger for more specialized analysts. The negative coefficients for *Specialization*, *Overlap - Type 2*, and *Overlap - Type 2* × *Specialization* reveal that specialization has an aggregate effect on performance, that information spillovers improve performance (as we have shown previously), but also that specialization amplifies the performance effects for spillovers. The results are consistent with specialization not only improving the ability of analysts to anticipate or analyze significant corporate events such as M&A, but also increasing their ability to coordinate with peers and take advantage of information spillovers.

5. Identification Concerns

Our results estimate how the productivity around a firm merger varies with how information is structured within an organization. The conclusion from these tests is that information spillovers increase analyst productivity and therefore that organization matters for individual productivity. In this section, we address identification concerns.

First, while we chose an observation window of up to two years prior and two years post the merger, it is possible that there are confounding events in the event window. This would be a problem if confounding events impacted forecast error non-randomly across analyst type. To mitigate this concern, we re-estimate our main results focusing on a window of up to six months prior and six months post the merger. In column (1) of Table 10, we present evidence showing that the main results hold.

Second, we examine mergers over the period 1984 to 2011. This period includes booms and busts, as well as hot and cold M&A waves. Consequently, we might not expect the change in forecast error around mergers to be constant through time. If the time-series variation in the change in forecast error is correlated with variation in coverage by analyst type, this might explain any results. Our main results address this in a couple of ways. We include calendar year and sector-year dummy variables throughout which capture aggregate and sector-specific time-series variation. Further, we include merger-specific characteristics in Tables 7 and 8. Nonetheless, in column (2) of Table 10 we present results in which we use abnormal change in forecast error as the independent variable. The abnormal change in forecast error is defined as the analyst change in scaled forecast error minus the average change in scaled forecast error for the acquirer firm across all analysts. Therefore, the abnormal forecast error absorbs the merger-specific mean change in forecast error and is equivalent to including merger fixed effects. Once again, the main results hold.

Third, the time period we study saw an improvement in technology, that might reduce communication costs, and also regulation that specifically targeted transparency in information disclosure to investors. On August 15, 2000, the SEC adopted Regulation FD to address the selective disclosure of information by publicly traded companies and other issuers. Specifically, Regulation FD mandates that when an issuer discloses material nonpublic information to certain individuals or entities, such as financial analysts, the issuer must make public disclosure of that information. In this way, the new rule aims to promote the full and fair disclosure. The passing of Regulation FD highlights the concern that results in the period prior to the rule might be due to selective disclosure. To mitigate the concerns that our results might be explained by selective disclosure and also that our results hold in later years when communication costs decreased, we re-run our main specification for the period 2000 – 2011 and present the results in column (3) of Table 10. Once again, the main results continue to hold.

6. Conclusion

In this paper we shed light on whether higher performing firms hire more productive individuals, or if higher performing firms create more productive individuals. We exploit the plausibly exogenous variation in the organization of information emanating from mergers of stocks that analysts follow to examine how information spillovers affect individual productivity. We provide evidence that performance, measured as forecast error, decreases around the merger, and that the decrease is lower when the analyst's own brokerage also covers the target firm consistent with information spillovers affecting individual productivity. The effects of information spillovers are stronger when analysts share the same geographical location, when peers are of a greater quality, and for related mergers, but are lower when there are greater coordination costs.

Using the population of equity analysts in brokerage-houses in the U.S. over a span of time as a natural laboratory to explore this question has two clear advantages: we observe analyst productivity (stock-level earnings forecast) and we observe individual performance measured by the accuracy of the earnings forecast. To identify the treatment effect of spillovers on productivity we compare performance around acquisitions for which the broker also covers the target with performance for which there is no coverage of the target for the same analyst working at the same brokerage. We propose that our within broker-analyst estimation of spillover effects absorbs selection effects that typically plague studies examining whether organization affects individual performance.

The findings of this paper shed light on the discussion of whether human capital is portable in research-based environments and highlight the importance of information and knowledge as a critical resource.

References

Agarwal, S. and R.Hauswald, 2010, "Distance and Private Information in Lending," *Review of Financial Studies*, 23 (7), 2757-2788.

Aghion, P., and J. Tirole. 1997, "Formal and Real Authority in Organizations," *The Journal of Political Economy*, 105 (1), 1–29.

Ahern, K.R., 2014, "Information Networks: Evidence from Illegal Insider Trading Tips," *University of Southern California*, Working Paper.

Bandiera O., I. Barankay and I. Rasul, 2005, "Social Preferences and the Response to Incentives: Evidence from Personnel Data," *The Quarterly Journal of Economics*, 120 (3), 917-962.

Betrand, M. and A. Schoar, 2003, "Managing with Style: The Effect of Managers on Firm Policies", *The Quarterly Journal of Economics*, 118 (4), 1169-1208.

Becker, G.S., 1973, "A Theory of Marriage: Part I," *The Journal of Political Economy*, 81 (4), 813-846.

Becker, G.S., 1993, *A Treatise on the Family*, Enlarged Edition, Harvard University Press.

Becker, G.S and K.M. Murphy, 1992, "The Division of Labor, Coordination Costs, and Knowledge," *The Quarterly Journal of Economics*, 107 (4), 1137-1160.

Beshears, J., 2013, "The Performance of Corporate Alliances: Evidences from Oil and Gas Drilling in the Gulf of Mexico," *Journal of Financial Economics*, 110 (2), 324-346.

Bloom, N., L. Garicano, R. Sadun and J.Van Reenen, 2014, "The Distinct Effect of Communication Technology and Information Technology on Firm Organization," *Management Science*, forthcoming.

Bolton, P., and M. Dewatripont, 1994, "The Firm as a Communication Network," *The Quarterly Journal of Economics*, 109 (4):809-830.

Brown, J. Z. Ivković, P. Smith, and S. Weisbenner, 2008, "Neighbors Matter: Causal Community Effects and Stock Market Participation,"*The Journal of Finance*, 63(3): 1509-1531.

Clarke, J., A. Khorana, A. Patel, and R. Rau, 2007, "The Impact of All-Star Analyst Job Changes on their Coverage Choices and Investment Banking Deal Flow," *Journal of Financial Economics*, 84, 713-737.

Coase, R.H., 1937, "The Nature of the Firm," Economica, 4 (16), 386-405.

Coase, R. H., 1988, "The Nature of the Firm: Origin, Meaning, Influence," *Journal of Law, Economics, and Organization*, 4.

Dunbar, C.G., 2000, "Factors Affecting Investment Bank Initial Public Offering Market Share," Journal of Financial Economics, 55, 3-41.

Garicano, L., 2000, "Hierarchies and the Organization of Knowledge in Production," *The Journal of Political Economy*, 108 (5), 874–904.

Garicano, L., and E. Rossi-Hansberg, 2006, "Organization and Inequality in a Knowledge Economy," *The Quarterly Journal of Economics*, 121 (4), 1383–1435.

Gil, R., J. M. Liberti, and J. Sturgess, 2014, "Authority and Initiative: Evidence from Bank Relationship Managers," Working Paper

Groysberg, B., Lee, L.E. & Nanda, A., 2008, "Can They Take it with Them?: The Portability of Star Knowledge Workers' Performance," Management Science, 54(7), 1213-1230.

Hart, O., 1989, "An Economist's Perspective on the Theory of the Firm", Columbia Law Review, 89(7), 1757-1774

Hong, H. and M. Kacperczyk, 2010, "Competition and Bias," The Quarterly Journal of Economics, 125 (4), 1683-1725.

Hong, H., J.D. Kubick and A. Solomon, 2000, "Security Analysts' Career Concerns and Herding of Earnings Forecasts," *Rand Journal of Economics,* 31 (1), 121-144.

Hong, H., J. D. Kubick and J. C. Stein, 2005. "Thy Neighbor's Portfolio: Word-of-Mouth Effect in the Holdings and Trades of Money Managers," *The Journal of Finance*, 60 (6), 2801-2824.

Kim, E.H., A. Morse and L. Zingales, 2009, "Are Elite Universities Losing their Competitive Edge?," *Journal of Financial Economics*, 93 (3), 353-381.

Klein, B., 1988, "Vertical Integration as Organizational Ownership: The Fisher Body-General Motors Relationship Revisited," *Journal of Law, Economics and Organization*, 4(1): 199–213.

Kothari, S.P., 2001, "Capital Markets Research in Accounting," Journal of Accounting and Economics, 31 (1), 105-231.

Krigman, L., W.H. Shaw, and K.L. Womack, 2001, "Why Do Firms Switch Underwriters?" Journal of Financial Economics, 60, 245-284

Landier, A., V.B. Nair and J. Wulf, 2009, "Trade-offs in Staying Close: Corporate Decision Making and Geographic Dispersion," *Review of Financial Studies*. 22 (3), 1119-1148

Lehavy, R., F. Li, and K. Merkley, 2011, "The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts," *The Accounting Review*, 86(3), 1087–1115

Leone, A. and J.S. Wu, 2007, "What Does it Take to Become a Superstar? Evidence from Institutional Investor Rankings of Financial Analysts?," University of Miami Working Paper

Liberti, J.M. and A.R. Mian, 2009, "Estimating the Effects of Hierarchies on Information Use," *Review of Financial Studies*, 22 (10), 4057-4090.

Liberti, J.M.,A. Seru and V. Vig, 2015, "Information, Credit and Organization," The University of Chicago Booth School of Business, Working Paper.

Mian, A.R., 2006, “Distance Constraints: The Limits of Foreign Lending in Poor Economies,” *The Journal of Finance*, 61 (3), 1465–1505.

Mullainathan, S. and D. Scharfstein, 2001, “Do Firm Boundaries Matter?,” *American Economic Review Papers and Proceedings,* 91(2), 195-199.

Petersen, M. and R.G. Rajan, 2002, “Does Distance Still Matter? The Information Revolution in Small Business Lending,” *The Journal of Finance*, 57 (6), 2533-2570.

Radner, R., 1993, “The Organization of Decentralized Information Processing,” *Econometrica*, 61 (5), 1109-1146.

Rajan, R.G. and L. Zingales, 1998, “Power in a Theory of the Firm,” The *Quarterly Journal of Economics*, 113 (2), 397-432.

Rajan, R.G. and L. Zingales, 2001, “The Firm as a Dedicated Hierarchy: A Theory of the Origins and Growth of Firms,” 116 (3), 805-852.

Seru, A., “Firm Boundaries Matter: Evidence from Conglomerates and R&D Activity,” *Journal of Financial Economics*, forthcoming.

Shimer, R. and L. Smith, 2000, “Assortative Matching and Search,” *Econometrica*, 68 (2), 343-369.

Skrastins, J., and V. Vig, 2014, “How Does Organizational Hierarchy Affects Information Production,” London Business School, Working Paper.

Stein, J., 2002, “Information Production and Capital Allocation: Decentralized Versus Hierarchical Firms,” *The Journal of Finance*, 57 (5), 1891-1921.

Stickel, S.E., 1995, “The Anatomy of the Performance of Buy and Sell Recommendations,” *Financial Analyst Journal*, 51 (1), 25-39.

Womack, K.L., 1996, “Do Brokerage Analysts’ Recommendations have Investment Value?,” *Journal of Finan*ce, 51 (1), 137-167.

Table 1: Descriptive Statistics: Real Mergers

This table reports descriptive statistics for the 2,403 real firm mergers used in the study. For each merger we present the size of the acquirer (*Acquirer Size*) and target (*Target Size*) market capitalizations, measured in millions of dollars in the quarter prior to the acquisition. *Target as % of Merged Firm* is the ratio $\frac{TargetSize}{AcquirerSize+TargetSize}$. *Sector Match* is a dummy variable equal to one if the acquirer and target share the same GICS industrial sector. *Acquirer Analyst Coverage* measures the number of analysts following the acquirer and *Target Analyst Coverage* measures the number of analysts following the stock in the period prior to the merger.

Variable	N	mean	StDev	Percentile 25^{th}	Percentile 50^{th}	Percentile 75^{th}
Acquirer Size ($MM)	2,403	11,781	38,411	692	2,047	7,013
Target Size ($MM)	2,403	1,975	6,702	95	285	1,055
Target as % of Merged Firm	2,403	0.20	0.18	0.05	0.15	0.32
Sector Match	2,403	0.68	0.47	0.00	1.00	1.00
Acquirer Analyst Coverage	2,403	16.10	11.11	8	13	22
Target Analyst Coverage	2,403	5.97	6.52	2	4	8

Table 2: Descriptive Statistics: Analyst Characteristics by Information Environment

This table reports descriptive statistics of the main variables used in our real-firm-merger setting. We track the change in analyst scaled forecast error for the acquirer around the merger, where the unit of observation is a analyst-stock pairing. The main dependent variable in our tests, ΔForecast Error$_{m,i}$, is the difference between the analyst-average forecast error after the merger and analyst-average forecast error before the merger, where m represents the acquirer stock and i represents the analyst. A positive ΔForecast Error$_{m,i}$ indicates that forecast error increased around the merger. We examine how ΔForecast Error$_{m,i}$ varies with the information environment facing the analyst. The information environment captures the degree of overlap in coverage of the acquire and target. The sample includes all analyst-stock pairs for which we observe variation in the information environment within a brokerage-analyst. The sample follows 2,878 brokerage-analyst pairings, composed of 2,394 analysts working for 215 brokers, covering 2,403 real firm mergers. This results in 15,939 analyst-stock pairs, of which 10,921 are in an information environment with no overlap in coverage (of the acquirer and target), and 5,018 are in an information environment with overlap in coverage. For the 5,018 pairs, 1,468 exhibit overlap at the brokerage-level only (i.e. overlap in coverage of the acquirer and target exists within the brokerage but is provided by two analysts), and 3,550 exhibit overlap at the analyst-level (i.e. overlap in coverage of the acquirer and target is from the same analyst within the brokerage). Type 1, 2, and 3 analysts refer to no overlap in coverage, overlap at the brokerage-level only, and overlap at the analyst-level, respectively. Firm-specific experience is the number of years the analyst has been covering the acquirer stock. Number of stocks covered is the number of stocks covered by the analyst. Number of sectors covered measures the number of GICS Sectors covered by the analyst. Based in New York City is a dummy variable if the analyst is based in New York. Acquirer Size and Target Size represent the market capitalization of the acquirer and target.Target as % of Merged Firm is the market capitalization of the target presented as a percentage of the market capitalization of the acquirer. Sector Match is a dummy variable equal to one if the acquirer and target are in the same GSECTOR.

				Overlap-level	
Information Environment	All	No Overlap (Type 1)	Overlap (Types 2 & 3)	Brokerage (Type 2)	Analyst (Type 3)
	(1)	(2)	(3)	(4)	(5)
#Analyst-Stock Pairs	15,939	10,921	5,018	1,468	3,550
Scaled Forecast Error$_i$	0.172	0.170	0.175	0.163	0.180
ΔForecast Error$_{m,i}$	0.058	0.067	0.037	0.078	0.019
Firm-Specific Experience	4.27	4.22	4.38	4.06	4.52
Number of Stocks Covered	18.61	18.64	18.54	16.50	19.38
Number of Sectors Covered	2.08	2.04	2.18	1.96	2.26
%Analysts Based in New York	0.27	0.26	0.29	0.30	0.29
Acquirer Size ($MM)	20,645	19,582	22,969	35,300	17,831
Target Size ($MM)	3,281	1,500	6,759	6,331	6,940
Target as % of Merged Firm	0.19	0.14	0.28	0.21	0.31
Sector Match	0.71	0.67	0.78	0.75	0.79

Table 3: Analyst Productivity and Information Environment

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. Estimations include broker fixed effects (column (2)), broker-analyst fixed effects (columns (3) - (5)), sector-year fixed effects (columns (4) and (5)), year fixed effects and time-varying analyst characteristics (columns (4) and (5)). The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$				
	(1)	(2)	(3)	(4)	(5)
Overlap	-0.054***	-0.057***	-0.042***	-0.038***	
	(0.008)	(0.008)	(0.008)	(0.008)	
Overlap - Type 2					-0.023*
					(0.013)
Overlap - Type 3					-0.045***
					(0.008)
Analyst Characteristics	No	No	No	Yes	Yes
Brokerage FE	No	Yes	No	No	No
Brokerage-Analyst FE	No	No	Yes	Yes	Yes
Sector-Year FE	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939	15,939
Adj. R^2	0.10	0.12	0.38	0.42	0.42

Table 4: Analyst Productivity and Information Environment: Institutional Size Effects

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on institutional size effects. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. *Large* captures the size of the brokerage at which the analyst is employed, measured as the *#Stocks* followed by the brokerage (column (1)), *#Analysts* employed by the brokerage (column (2)), *#Sectors* covered by the brokerage (column (3)), or whether the brokerage is based in *New York*. Estimations include broker-analyst fixed effects, sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$			
Large =	#Stocks	#Analysts	#Sectors	New York
	(1)	(2)	(3)	(4)
Overlap - Type 2	-0.018*	-0.017*	-0.025*	-0.023*
	(0.011)	(0.010)	(0.013)	(0.013)
Overlap - Type 3	-0.045***	-0.045*	-0.045**	-0.045**
	(0.008)	(0.008)	(0.008)	(0.008)
Overlap - Type 2 × Large	-0.027*	-0.028*	-0.045*	-0.057**
	(0.015)	(0.016)	(0.027)	(0.026)
Overlap - Type 3 × Large	0.005	0.005	0.021	0.016
	(0.010)	(0.010)	(0.022)	(0.017)
Analyst Characteristics	Yes	Yes	Yes	Yes
Brokerage-Analyst FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939
Adj. R^2	0.42	0.43	0.42	0.43

Table 5: Analyst Productivity and Information Environment: The Role of Spillovers

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on location and team size. For each analyst-stock pair, we measure Δ*Forecast* $Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. *Location* captures whether the Type 2 analyst works for a broker with a single location (column (1)) or whether Type 2 analyst and peer following the target sit in the same location (column (3)). *Team Size* is measured as the natural logarithm of the number of analysts working within the acquirer's GICS industrial sector at the analyst's brokerage. *#Analysts* is the number of analysts employed by the brokerage. Estimations include broker-analyst fixed effects, sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast $Error_{m,i}$			
	Location= Single	Location= Same	Team Size	
	(1)	(2)	(3)	(4)
Overlap - Type 2	-0.020*	-0.016	-0.030**	-0.021*
	(0.012)	(0.011)	(0.013)	(0.013)
Overlap - Type 2 × Location	-0.041**	-0.036**		
	(0.020)	(0.022)		
Overlap - Type 2 × Team Size			0.024*	0.039***
			(0.014)	(0.015)
Overlap - Type 2 × #Analysts				-0.044***
				(0.16)
Team Size			0.017	0.16
			(0.022)	(0.022)
Overlap - Type 3	-0.045***	-0.045***	-0.045***	-0.045***
	(0.009)	(0.009)	(0.009)	(0.009)
Analyst Characteristics	Yes	Yes	Yes	Yes
Brokerage-Analyst FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939
Adj. R^2	0.42	0.42	0.42	0.42

Table 6: Analyst Productivity and Information Environment: The Role of Skill

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on analyst skill. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. We identify analysts that are All-Star analysts (*All-Star*) and whether the peers that cover the target alongside the Type 2 analyst are All-Stars (*Overlap - Type 2: Peer is All-Star*) as those analysts who were named to the *Institutional Investors All-America Research Team* in a given year, commonly known as *All-Star Analysts*. Estimations include broker-analyst fixed effects, sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$		
	(1)	(2)	(3)
Overlap - Type 2	-0.023*	-0.019*	-0.020*
	(0.013)	(0.012)	(0.012)
Overlap - Type 3	-0.045***	-0.042***	-0.045***
	(0.009)	(0.009)	(0.009)
All-Star	0.007	0.020	
	(0.025)	(0.028)	
Overlap - Type 2 $\times$ All-Star		-0.059**	
		(0.030)	
Overlap - Type 3 $\times$ All-Star		-0.011	
		(0.013)	
Overlap - Type 2: Peer is All-Star			-0.032
			(0.032)
Analyst Characteristics	Yes	Yes	Yes
Brokerage-Analyst FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	15,939	15,939	15,939
Adj. R^2	0.42	0.42	0.42

Table 7: Analyst Productivity and Information Environment: Information Content of Merger

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on the information content of the merger. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. In columns (1) - (4) we examine the scope of the merger by identifying *Related Mergers* as those mergers where the acquirer and target share a GICS industrial sector. In columns (5) - (8), we examine the relative size of the target and acquirer and focus on *Target as % of Merged Firm*, which is the ratio $\frac{TargetSize}{AcquirerSize+TargetSize}$. Estimations include broker-analyst fixed effects (except columns (1) and (5)), sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$							
	Information =							
	Related Merger				Target as % of Merged Firm			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Information	-0.026***	-0.020**	-0.019**	-0.021**	-0.024	-0.041	-0.008	0.032
	(0.008)	(0.008)	(0.008)	(0.010)	(0.026)	(0.027)	(0.029)	(0.042)
Overlap - Type 2			-0.022*	-0.024*			-0.021*	-0.022*
			(0.013)	(0.013)			(0.013)	(0.013)
Overlap - Type 3			-0.046***	-0.060***			-0.044***	-0.032***
			(0.009)	(0.012)			(0.010)	(0.012)
Overlap - Type 2 × *Information*				-0.035*				-0.149*
				(0.021)				(0.078)
Overlap - Type 3 × *Information*				0.028*				-0.070
				(0.017)				(0.057)
Analyst Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage-Analyst FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939	15,939	15,939	15,939	15,939
Adj. R^2	0.18	0.42	0.42	0.42	0.18	0.42	0.42	0.42

Table 8: Analyst Productivity and Information Environment: Aggregate Analyst Coverage

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on aggregate analyst coverage. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. *Acquirer Analyst Coverage* measures the number of analysts following the acquirer and *Target Analyst Coverage* measures the number of analysts following the stock in the period prior to the merger. Estimations include broker-analyst fixed effects (except column (1)), sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$				
	(1)	(2)	(3)	(4)	(5)
Target Analyst Coverage	-0.003***	-0.002***	-0.002***	-0.001**	-0.003***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0009)
Acquirer Analyst Coverage			0.0002		
			(0.0005)		
Overlap - Type 2				-0.019*	-0.012
				(0.012)	(0.012)
Overlap - Type 3				-0.034***	-0.045***
				(0.010)	(0.014)
Overlap - Type 2 × Target Analyst Coverage					-0.001
					(0.002)
Overlap - Type 3 × Target Analyst Coverage					0.004***
					(0.001)
Analyst Characteristics	Yes	Yes	Yes	Yes	Yes
Brokerage-Analyst FE	No	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939	15,939
Adj. R^2	0.39	0.42	0.42	0.43	43

Table 9: Analyst Productivity and Information Environment: The Role of Specialization

This table reports OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on specialization. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. *Specialization* is the degree of specialization the analyst has in following stocks, and is measured as the natural logarithm of the number of firms the analyst follows per sector (a greater of firms per sector is greater specialization). Estimations include broker-analyst fixed effects (except column (1)), sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$			
	(1)	(2)	(3)	(4)
Specialization	-0.023**	-0.030**	-0.030**	-0.027**
	(0.010)	(0.015)	(0.015)	(0.015)
Overlap - Type 2			-0.023*	-0.023*
			(0.013)	(0.013)
Overlap - Type 3			-0.045***	-0.045***
			(0.008)	(0.008)
Overlap - Type 2 × Specialization				-0.025*
				(0.013)
Overlap - Type 3 × Specialization				-0.002
				(0.012)
Analyst Characteristics	Yes	Yes	Yes	Yes
Brokerage-Analyst FE	No	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,939	15,939	15,939	15,939
Adj. R^2	0.18	0.42	0.42	0.42

Table 10: Identification Concerns

This table reports results addressing identification concerns for OLS estimates of analyst performance around real firm mergers, measured as the change in forecast error Δ*Forecast Error*, on specialization. For each analyst-stock pair, we measure $\Delta Forecast\ Error_{m,i}$ as the difference in the mean forecast error post merger and the mean forecast error post merger for the analyst-stock pair. Forecast error is defined as the absolute difference between the announced earnings-per-share (EPS) and analyst i's most recent EPS forecast, divided by the stock price as of the corresponding fiscal quarter end; we require EPS forecasts to be issued/updated at least once in the three months prior to the earnings announcement. We compute the scaled forecast error for quarterly earnings announced in the two year-window around the effective date of the merger. Both Forecast Error and Δ*Forecast Error* are reported as a percentage. *Overlap* captures whether an analyst at the brokerage also covers the target. *Overlap* is a dummy variable equal to one if there is an overlap in coverage of the target for merger m at brokerage j where analyst i follows the acquirer. *Overlap - Type 2* captures analyst for which the overlap is at the brokerage level while *Overlap - Type 3* analysts exhibit overlap at the brokerage and individual level. In column (1), we repeat the main estimation, but take the average forecast error pre- and post-merger over six months only. In column (2), the dependent variable is *Abnormal* Δ*Forecast Error*, which is the difference between the analyst's Δ*Forecast Error* and the cross-sectional average Δ*Forecast Error* for the merger. In column (3), we estimate results for the period 2000 - 2011. Estimations include broker-analyst fixed effects, sector-year fixed effects, year fixed effects and time-varying analyst characteristics. The analyst characteristics include the stock-specific experience of the analyst, the number of stocks the analyst follows, the number of sectors the analyst follows, and the size of the analysts team. Fixed effects are denoted as FE. Standard errors are reported in parentheses and are computed after allowing for correlation in a given broker-analyst. *, ** and *** represent statistical significance at the 10, 5 and 1 percent levels.

Dependent Variable:	ΔForecast Error$_{m,i}$		
	-/+ 6th Obs.	Abnormal ΔFE	Post 2000
	(1)	(2)	(3)
Overlap - Type 2	-0.024*	-0.008*	-0.033*
	(0.014)	(0.005)	(0.020)
Overlap - Type 3	-0.030***	-.0149***	-0.066***
	(0.009)	(0.005)	(0.018)
Brokerage-Analyst FE	Yes	Yes	Yes
Analyst Characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	15,939	15,939	5,059
Adj. R^2	0.30	0.31	0.49