Geographic Proximity and IPO Firm Coverage

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Abstract

Using a sample of 4,459 analysts covering 3,035 US IPOs during 1996 – 2009, we find that that analysts are 67% more likely to cover IPO firms located within their home states than those located in other states. Geographic proximity matters most for non-underwriter analysts and for those with less industry expertise. Proximate analysts also initiate their coverage of IPO firms earlier. The effect of geographic proximity on analysts' coverage likelihood and promptness is more prominent for smaller firms, firms with less institutional involvement and those producing more unique products. The presence of local analysts helps attract other analysts to cover the underlying firms, serving as a leap toe to increased visibility of the IPO firms.

Analysts provide valuable information about the firms they cover and play an important role in monitoring managers. Abundant evidence reveals that analyst coverage affects price informativeness, earnings management, financing activities, firm value, and cost of capital (see, e.g., Brennan, Jegadeesh and Swaminathan (1993), Irvine (2003), Best, Payne, and Howell (2003), Roulstone (2003), Lang, Lins, and Miller (2004), Chang, Dasgupta, and Hilary (2006), and Yu (2008)).[1] The consensus emerging from this literature is that analyst coverage matters to public firms, especially to those with less visibility to the public, less transparent information environments and more severe agency problems. In fact, some managers value the analyst coverage so much that they are even willing to pay a fee-based research firm to cover their companies. Based on a unique data of over 500 US companies, Kirk (2010) documents that firms with greater uncertainty, weaker information environments, and low turnover are more likely to buy analyst coverage.

Analyst activity matters as well to brokerage houses and investment banks, the major employers of sell-side analysts. Irvine (2001), Jackson (2005), and Niehaus and Zhang (2008) find that a broker's market share of trading volume on a stock increases after research coverage by its analyst. Krigman, Shaw, and Womack (2001) report survey evidence that improved research coverage is the most important element in the decision to switch underwriters between firms' initial public offerings (IPOs) and their subsequent seasoned equity offerings. Derrien (2006) finds that analysts can increase their employers' chances of managing or co-managing future IPOs by issuing generous recommendations to recent IPOs.

Motivated by the importance of analyst coverage to companies and to analysts' employers, a substantial literature investigates how firms gain analyst coverage. Bhushan (1989) finds that analyst following increases with firm size, institutional ownership, and return variability. O'Brien and Bhushan (1990) find that analyst coverage increases when a firm's stock return volatility has declined, and when a firm has lower prior analyst coverage. McNichols and O'Brien (1997) find that analysts tend to initiate coverage of a firm when they are relatively optimistic regarding its future performance. Barth, Kasznik, and McNichols (2001) show that analyst coverage increases with firms' intangible assets. Lang, Lins,

[1] Ramnath, Rock, and Shane (2008) review the recent analyst forecast literature.

and Miller (2004) find that analysts are less likely to follow firms with potential incentives to withhold or manipulate information, and this relation is stronger for firms from low shareholder protection countries.

We examine the impact of geographic proximity on the analyst's coverage decision for a group of U.S. IPO firms. Our interest in the IPO setting arises from the observation that analyst coverage exhibits strong persistence (McNichols and O'Brien, 2001): analysts who have covered a firm in the past tend to continue doing so. This observation gives importance to the analyst's decision to initiate coverage for a firm. IPO firms provide a relatively clean setting in which to consider coverage initiations, because in general the coverage opportunity begins at the IPO. We believe IPOs also provide a powerful setting for testing our conjectures about geographic proximity, because of the importance of coverage to newly public firms. Lacking price history and (typically) pre-prospectus financial data, IPO firms need to bridge a considerable information gap to reach investors. This relative scarcity of information suggests both that IPO firms may seek analyst coverage, and that investors may seek covered firms. On the other hand, effort-averse analysts may find the high cost of gathering data on IPO firms an impediment to providing coverage. We expect geographic proximity to be especially important in this low-information setting.

Following Bhushan (1998), we presume the analyst bases the decision to initiate coverage on a tradeoff between costs and benefits of following a particular firm.[2] McNichols and O'Brien (2001) conjecture that factors such as the cost of learning and gathering information and the ability to make company-specific links may affect analyst following. Both academic and anecdotal evidence suggests that geographic proximity affects analyst forecast accuracy (see Dunn and Nathan (1998), Malloy (2005), and Bae, Stulz, and Tan (2008)). We conjecture that these factors also lower analysts' costs of providing coverage.

We extend the previous literature in the following ways. First, we analyze coverage initiations at the level where the decision is made: an individual analyst covering a specific firm. Most research about

[2] Analysts' employers, mainly brokerage houses and investment banks, undoubtedly make some coverage decisions, especially for new analysts. In this case, our results suggest that these employers consider the location and expertise of the individual analyst in assigning firms to them. While keeping this alternative interpretation in mind, henceforth we discuss the analyst as the decision-maker.

the determinants of analyst coverage, including the papers cited above, relates the total number of analysts following a firm to the firm's characteristics and sometimes market- or country-level characteristics. Some papers also examine brokerage house or analyst characteristics, such as research quality (Tehranian, Zhao and Zhu (2010)) or All-Star status (Li, Rau, and Xu (2009)), as determinants of coverage. The costs of following a new firm relate not only to firm, analyst and brokerage characteristics viewed separately, but also to the alignment between analyst and firm. Few papers, however, examine links between specific analysts and firms. The exceptions, to our knowledge, are Liang, Riedl, and Venkataraman (2008) and Bae, Tan, and Welker (2008). Liang, Riedl, and Venkataraman (2008) find that analysts tend to follow firms in industries where the analysts have expertise, and those with coverage by relatively inexperienced analysts. Our results confirm their first result and extend it to a different setting. Bae, Tan, and Welker (2008) find that analysts tend to cover foreign firms from countries with accounting standards that are relatively similar to those of the analysts' country. Since we limit our sample to U.S. IPOs, the issue of different accounting standards does not arise in our setting.

Secondly, we contribute to the literature investigating the impact of distance on various market participants such as institutional and individual investors, financial analysts and brokers. This literature implies that the cost of acquiring information increases with geographic distance, and motivates our exploration of geography as a factor in analysts' coverage decisions. Lastly, our research contributes to the literature on analyst coverage for IPO firms. We conjecture that geographic distance adversely affects analysts' willingness and capability to gather information on IPO firms. We expect to find an association between geographic proximity and analysts' decisions to cover IPOs. To our knowledge, no study explicitly examines the impact of geographic proximity on analysts' coverage likelihood and promptness for IPO firms.

We find that geographic proximity greatly increases the likelihood that analysts will initiate coverage of IPO firms. Our model of the coverage decision shows that analysts are 67% more likely to cover IPO firms located in their home states than those in other states. The effect of geographic proximity on analysts' coverage likelihood is more prominent for non-specialists and non-underwriter analysts. In our results on coverage timing, we find that local analysts initiate coverage on IPO firms more promptly than distant analysts. Further analyses show that geographic proximity accelerates coverage only for non-underwriter analysts. These findings suggest that geographic proximity matters in analysts' coverage decisions, especially for non-underwriter analysts and non-specialists. We also examine whether firm traits and analysts' prestige have any effect on the relationship between analysts' geographic proximity and their coverage decisions. We find that the effect of geographic proximity on analysts' coverage likelihood and promptness is more pronounced for smaller firms, firms with less institutional involvement and those producing more unique products. Analysts' prestige to a certain degree moderate the effect of geographic proximity in their decision to cover IPOs, but accelerate their coverage initiations once they decide to follow these firms.

An interesting issue is whether the influence of geographic proximity on analyst coverage decisions has real effects for the underlying firms. One channel for local analyst coverage to affect the target IPOs is to bring along other analysts who would have otherwise neglected these firms. We keep IPO firms that are either covered exclusively by local analysts or not covered by any analysts within half a year immediately after the IPO date, and then track these firms for analyst coverage within the next one year. We find that prompt coverage by local analysts after IPO date attracts other analysts to jump into the boat. Thus the presence of local analysts serves as a leap toe to increased visibility of the IPO firms.

The rest of the paper is organized as follows. In the next section, we review the related literature and develop our main hypotheses. Section II describes our data sources and sample criteria. Section III conducts empirical analyses. Section IV examines the implications of local analyst coverage. Section V provides robustness checks, and Section VI concludes.

I. Related literature and hypotheses

There is a large literature on the impact of geographic proximity on various market participants. Coval and Moskowitz (1999) find that mutual fund managers overweight the stocks of firms located closer to them. Coval and Moskowitz (2001) find that mutual fund managers are better at picking stocks of nearby firms than those of distant firms. Shultz (2003) finds that regional brokers are more likely to make markets in the local stocks that their customers own in disproportionate amount. Kedia and Zhou (2007) show that a large presence of local market makers significantly reduces both quoted and effective spreads. Butler (2007) concludes local underwriters are able to offer municipal bond issuers more competitive pricing as a result of reduced informational asymmetries. Uysal, Kedia, and Panchapagesan (2008) show that local acquirers have higher returns in mergers and acquisitions. Ivkovic and Weisbenner (2005) document that individual households are able to process and exploit locally available information to earn excess returns. In contrast, Seasholes and Zhu (2009) find that purchases of local stocks significantly underperform sales of local stocks. Pirinsky and Wang (2010) provide a review of the literature on the relationship between firm geographic location and corporate finance.

Previous studies have shown that the level of analyst following relates to firm size, institutional ownership, intangible assets, stock performance, return variability, and accounting standards (see Bhushan (1989), O'Brien and Bhushan (1990), McNichols and O'Brien (1997), Barth, Kasznik, and McNichols (2001), Hope (2003), Bae, Tan, and Welker (2008)). There are a handful of papers that relate geographic distance to analysts' forecast performance. For example, Malloy (2005) and Bae, Stulz and Tan (2008) find that analysts located closer to a firm have more accurate earnings forecasts. Chang (2003) compares the stock recommendations of foreign and expatriate analysts for Taiwanese firms and finds a local advantage in that expatriate analysts outperform foreign analysts, but he also finds that expatriate analysts outperform local analysts working for domestic firms.

There is a literature on analyst coverage for equity offering firms. Rajan and Servaes (1997) investigate the link between analyst optimism and IPO anomalies of short-term underpricing and long-run underperformance, and find that underpricing leads to increased analyst following. Bradley, Jordan, and Ritter (2003) and Cliff and Denis (2004) find that the lead underwriter typically provides research coverage within one year of the offer date. O'Brien, McNichols, and Lin (2005), McNichols, O'Brien, and Pamukcu (2007) and Bradley, Jordan, and Ritter (2008) find that underwriter analysts initiate recommendations on equity offering firms more quickly than non-underwriter analysts. Clarke, Khorana, Patel, and Rau (2007) find that when an All-star analyst changes jobs, she is more likely to retain or add coverage of larger glamour firms that have pre-existing investment banking relationships with her new employer. Das, Guo, and Zhang (2006) find that IPOs with unexpectedly high analyst coverage have better operating and return performance than those with lower coverage than expected, consistent with McNichols and O'Brien's conjecture that analysts selectively provide coverage on firms with favorable future prospects. James and Karceski (2006) find results consistent with underwriter analysts providing a "booster shot" of favorable coverage to poorly performing IPOs.

A few studies document that analyst industry knowledge are important for analyst activities. Previts and Bricker (1994) use content analysis to examine 479 analyst reports and find that analysts employ a strategy of disaggregating firm-level information into segments. Jacob, Lys, and Neale (1999) find that analysts' forecast accuracy improves with analyst-company alignments and industry specialization, but not with general experience. Botosan and Harris (2000) report that analyst following increases with firms' decisions to include information on segment activity as part of their quarterly reports. Gilson, Healy, Noe and Palepu (2001) find that firms emerging from conglomerate stock breakups experience a significant increase in coverage by analysts that specialize in the subsidiary firms' industries. They also find that forecast improvements for specialists exceed those for non-specialists.

Analysts face a trade-off between earnings forecast timeliness and forecast accuracy. They could issue forecasts immediately in response to new information, or wait for additional information/analysis to provide more accurate forecasts. Cooper, Day and Lewis (2001) find that the price response to timelier forecast revisions is higher than the price response to those of follower analysts, suggesting that investors value timeliness more than *ex post* forecast accuracy. Mozes (2003) finds that timely forecasts improve on existing forecasts, although they are less accurate *ex post*. To the extent that forecast timeliness is an important performance criterion, analysts are motivated to initiate their coverage earlier once they have decided to cover the target firms.

We conjecture that the cost of following a firm decreases with analysts' proximity to the firm. Rogers and Grant (1997) examine 187 analyst reports and find that only about one-half of the information in the analysts' research reports could be found in the corresponding corporate annual reports, suggesting analysts' heavy use of other channels to collect information. Analysts located close to target firms may enjoy more timely visits to firms' operating sites, and also may have better access to information because they can talk to firm management in person. Alternatively, they might talk to local employees, customers, and competitors of the target firms to collect first-hand information. Thus, we expect that analysts are more likely to cover proximate firms, *ceteris paribus*. Motivated to provide prompt coverage, analysts will initiate coverage on proximate firms earlier if proximity facilitates their information collection and processing capability.

Our hypotheses, stated below in alternative form, reflect our primary conjecture that the costs of following IPO firms decrease with the analysts' proximity to the target firms.

H1: Local analysts are more likely to initiate coverage on IPO firms.

H2: Local analysts who initiate coverage on IPO firms do so earlier than distant analysts.

II. Data

In this section we describe our data sources and criteria for constructing our samples. We also provide computation details for geographic proximity. We show summary statistics for the final samples along with information about the geographic distribution of sample IPO firms and analysts. Table I describes the variables used in this study and the data sources. [INSERT TABLE I]

A. Sample construction

We begin our sample selection by identifying 4,126 U.S. firms with an IPO of common stock during 1996 to 2009 from the Thomson One Banker Deal database. From the same database, we also obtain the city and state location of firm headquarters, information on the offering (issue date, middle of filing price, offer price, presence of venture capitalists, identity of book managers/co-managers), and price change between offer and closing price at one day, six months, and one-year post-IPO.

We match the IPO sample to the I/B/E/S detail file by CUSIP, and obtain all analyst forecasts within two years after the IPO date during 1996-2010.[3] As Appendix A shows, we lose 287 IPOs with no

[3] Our I/B/E/S data extend through January 2010, so some IPOs during 2008-2009 will not have a full two years after the IPO dates.

CUSIP match on I/B/E/S, and a further 97 IPOs for missing return information from CRSP. We exclude a further 37 IPOs that were covered by analysts within three years prior to IPO issue date, because firms going public again after briefly going private do not necessarily represent new coverage opportunities by the analysts. We delete 12 IPOs that we cannot find their latitude and longitude information. We define a coverage initiation as the first post-IPO forecast of the next-year annual earnings per share by each analyst that we could identify her city location based on the Nelson's Directory of Investment Research. For 661 deals, we find no analyst coverage initiation within two years post IPO date. Our final sample includes 4,459 distinct analysts with a total of 20,715 coverage initiations for 3,035 IPO deals.[4] We refer to this sample as the *coverage sample*.

We use the I/B/E/S broker translation file to obtain names for analysts and brokers included in the I/B/E/S detail file. We then follow the same procedure as Bae, Stulz, and Tan (2008) and Bae, Tan, and Welker (2008) to match these broker and analyst names to those from the annual volumes of the Nelson's Directory of Investment Research, to obtain city and state locations and star status for I/B/E/S analysts. The analyst-matching rate between I/B/E/S and Nelson's Directory averages 82% in our sample, and ranges by year from 63% to 92%, as shown in Table II.

B. Choice sample

For our Cox regression and Tobit analysis of coverage initiation timing, we limit our attention to analysts who have initiated coverage on the firm within two years of the IPO date, as described above. To study the decision to initiate coverage, we also include analysts who chose not to cover a given firm. Of the 4,459 analysts in the coverage sample, 1,173 cover only a single IPO firm, and 751 cover only two IPO firms during our sample period. Including analysts who cover few IPOs in our sample may impede the ability to identify their motives empirically. For this reason, and to keep the sample to a manageable size, when we study the likelihood of coverage initiation we restrict our attention to the 1,538 analysts who cover at least five sample firms within two years after IPO dates. For each of these analysts and the 2,857 IPO firms they cover, we include an analyst-firm pair in our likelihood analysis if and only if the

[4] This represents 3,033 distinct IPO firms.

analyst covers other firms in the I/B/E/S database during the first six months after the given firm's IPO. This eliminates analysts with no possibility of coverage around the time of the firm's IPO, because they are not working as analysts at that time. This process yields 2,356,038 observations. We refer to this sample as the *choice sample*. We set the indicator variable *cover* equal to one if a given analyst covers a given IPO firm, and zero otherwise. Of the 20,715 initiations in the coverage sample described in the previous section, 14,639 are by analysts that have covered at least five sample IPO firms. These represent 0.62% of the choice sample.

As a robustness check, we repeat our analyses using alternative samples. We include all analysts that have covered any of the 3,035 sample IPO firms within two years post-IPO. This full sample contains 4,459 distinct analysts with 20,715 coverage initiations during 1996 - 2010. The corresponding choice sample consists of 5,494,760 observations. To address the potential confounding effects of brokerage size or prestige, we analyze a sample restricted to analysts working with the top 20 brokers in terms of the number of analysts that have covered at least one sample IPO firm during 1996-2010, and the IPO firms covered by these analysts.[5] Appendix C lists these Top-20 sample brokerages, which contains 2,276 distinct analysts with 10,319 coverage initiations on 2,591 IPO firms during 1996 - 2010. The corresponding choice sample consists of 2,678,106 observations. Appendix B shows that among the Top-20 sample brokerages, Credit Suisse First Boston covers the largest number of IPO firms, followed by Banc of America Securities LLC and Citigroup, each covering nearly 600 IPOs.

C. Proxies for geographic proximity and control variables

We hypothesize that analysts close to an IPO firm are more likely to initiate coverage, and to do so more quickly. We employ two proxies for analyst proximity. Our first proxy is a dummy variable indicating whether the analyst and the firm are from the same sate. The second proxy is the geographic distance between the analyst and the firm. To compute geographic proximity we need to know both analyst location and firm location. The Thomson One Banker Deal database provides city and state locations of firm headquarters, while Nelson's Directory of Investment Research provides city and state

[5] Our results are similar if we restrict the population of analysts to those working with the top 50 brokers.

locations of analysts. We construct an indicator variable, *local*, equal to one if an analyst is located in the same state as the firm, and zero otherwise. We also obtain latitudes and longitudes for cities based on the 1990 and 2000 Census Gazetteer Files available from the U.S. Census Bureau website.[6] For analysts located outside the U.S., we search Google for the latitudes and longitudes of their city locations. We then compute the distance in kilometers between analysts and firms based on the latitudes and longitudes of the cities.[7] In multivariate analyses we transform the geographic distance into natural log form.

We obtain the identity of book managers/co-managers for each IPO firms from Thomson One Banker Deal database. We then merge the broker names to those in the I/B/E/S and create an indicator variable *underwriter* that is equal to one if an analyst's employer is a manager or co-manager of the firm's IPO, zero otherwise. We follow Gilson et al. (2001) to classify analyst specialists. For each analyst-firm pair, we compute the number of firms covered by the analyst in the year prior to the IPO date with the same I/B/E/S industry code as the IPO firm, based on the whole I/B/E/S universe (both US detail files and international detail files). We classify an analyst as a *specialist* if she covers at least five firms in the IPO firm's industry.[8] Table I describes other control variables used in this study and the data sources.

D. Summary statistics

Table II Panel A presents the yearly distribution and deal characteristics for all the IPO firms during 1996 – 2009. There are a total of 3,696 IPOs with non-missing control variables, with 3,035 being covered within two year after the IPO dates. We observe that the number of IPOs covered by analysts is the highest in 1996 at 617, while the number of active analysts peaks in 1999 at 1,486, both fall off dramatically during 2001 to 2003 to fewer than 100 IPOs covered by approximately 500 analysts. The drop-off reflects the stagnant public offering market after the technology crash in 2000, and a corresponding restructuring in the financial analyst industry.[9] [INSERT TABLE II]

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[6] http://www.census.gov/geo/www/gazetteer/gazette.html
[7] We used the Great Circle Distance algorithm at http://www.meridianworlddata.com/distance-calculation.asp.
[8] Our main results are robust to using four or six firms as the cutoff for *specialist*.
[9] See Kadan, Madureira, Wang, and Zach (2009) for a detailed discussion of new regulations on financial analysts in the early 2000s.

Table II Panel A shows that our procedure for matching brokers and analysts between I/B/E/S and Nelson's Directory of Investment Research succeeds in identifying on average 82% of I/B/E/S analysts for our sample IPO firms over the years. we are able to match 92% of I/B/E/S analysts to Nelson's Directory in 2002, but our matching rate drops since 2005. This drop occurs because I/B/E/S stopped providing a broker translation file, which is our main source for broker and analyst names in the I/B/E/S data. [10]

Consistent with previous literature Rajan, we find IPO firms underpriced, with a first-day run-up averaging 16.53% of the offer price. The underpricing is especially pronounced in 1999 and 2000, when underpricing averages 64.46% and 54.36%, respectively. The price adjustment of offer price relative to the initial filing price averages -0.1%, but exhibits considerable variation across years, with 1999 and 2000 values of 17.27% and 11.43% respectively. Our IPO firms' market value at IPO date average $639 million. Venture capitalists back 30% of our sample firms, on average.

Table II Panel B shows IPO firms' and analysts' locations by state in the sub-sample we use for our main analyses, 2,857 IPO firms and 1,538 analysts covering at least 5 IPOs. California has 770 IPO firms, representing 26.95% of our sample firms, followed by Texas, New York, Massachusetts, Florida and Illinois, each with more than 100 IPO firms. New York is home to the largest concentration of analysts covering these IPO firms, with 767 analysts, representing 42.33% of the subset of analysts who have covered at least 5 IPOs. California, Massachusetts, Minnesota, Illinois and Virginia each has more than 50 analysts.

Figure 1 shows the number of IPO firms with analyst coverage initiations by distinct analysts, the number of analyst coverage initiations by all analysts, and the number of analyst coverage initiations by local analysts during each period of 20 days after IPO date. For each firm within two years after IPO date, we keep only the first earnings forecast for each analyst that are identified with geographic locations based on the Nelson's Directory of Investment Research. We find there is a sudden burst of analyst

[10] We obtained our broker translation file directly from I/B/E/S in September 2005. We assume analyst affiliations with brokers do not change after 2005, and supplement I/B/E/S analyst names and their broker affiliations from the recommendation detail file after 2005.

coverage initiations in the second and third twenty-day periods post IPO date. There are coverage initiations on more than 1,500 and 1,300 firms in the second and third period, respectively, compared with an average of fewer than 400 firms for the other periods. There are more than 3,000 coverage initiations in each of these two period, representing 31% of the total number of coverage initiations in our sample. The coverage initiations in both periods are each more than seven times of the average number of coverage initiations in the other periods. There are over 739 and 550 coverage initiations by local analysts in the second and third period, respectively, which in combination account for 33% of total number of coverage initiations by the local analysts in our sample. Analyst coverage initiation is fairly stable three months after IPO date. [INSERT FIGURE 1]

III. Empirical Analysis

A. Univariate Analysis

In unreported correlation table, we find that geographic proximity relates positively to analyst coverage initiation and negatively to the time interval between IPO date and coverage initiation date, consistent with our conjecture that geographic proximity influences analyst coverage. Previous literature shows that analyst underwriting relationship and industry specialty have a predominant impact on their coverage activities, we next investigate the impact of geographic proximity after controlling for either underwriting relationship or industry specialty.

Table III Panel A shows the average coverage ratio within analyst groups based on *local*, *specialist* and *underwriter* for the choice sample, and Panel B shows average days to initiate coverage within the same analyst groups for the coverage sample. For both Panel A and B, we restrict our attention to the 1,538 analysts who have covered at least five IPO firms. As we describe in Table I, we define analyst *specialist* as those who cover at least five firms in the same I/B/E/S industry as the given firm in the year prior to firm's IPO date, and *underwriter* analysts as those working for either lead managers or co-managers of the IPO. [INSERT TABLE III]

In Panel A of Table III, we observe that industry specialization has a more than nine-fold effect on coverage rates (e.g. 7.43% vs. 0.77% for specialists vs. non-specialists among local analysts), and underwriter status has a more than fourfold effect (e.g. 4.83% vs. 0.86% for underwriters vs. non-underwriters among local analysts), in all pair-wise comparisons. Geographic proximity has a more modest but measurable effect, ranging from a 50% increase (4.96% vs. 7.43% for non-local vs. local specialist analysts) to more than doubling the coverage rate (0.38% vs. 0.86% for non-local vs. local non-underwriter analysts), in all subgroups.

In Panel B, we observe that industry specialist analysts initiate coverage on average three to four months earlier than non-specialists (e.g. 165 vs. 267 days for specialists vs. non-specialists among local analysts). Underwriter analysts initiate coverage on average four to six months earlier than non-underwriter analysts (e.g. 124 vs. 296 days for underwriters vs. non-underwriters among non-local analysts). Being local to the IPO firm accelerates coverage for both specialists and non-specialists. It also accelerates coverage by about three weeks for non-underwriter analysts, but has a negligible effect on underwriter analysts. In sum, Panel A and B of Table III show that geographic proximity affect both analyst coverage likelihood and timing. However, the effects of underwriting relationship and analyst industry specialty dominate that of geographic proximity.

In Panel C we compare analyst-firm level traits between the covered and the non-covered subsamples in the choice sample, which contains 2,356,038 analyst-firm pairs, of which 14,639 represent coverage. We first compute the mean for each analyst across firms in that analyst's covered and non-covered portfolios, and then compute the mean and median across analysts for the covered and non-covered subsamples, respectively. On average, 20% of the analysts in the covered set are *local*, as compared with 11% in the non-covered set. The average distance from an analyst to a covered firm is 1,126 kilometers, versus 1,305 kilometers to a non-covered firm. Analysts have on average 42% industry expertise in covered firms and 38% are industry specialists, compared with 7% industry expertise and 4% industry specialists in non-covered firms. All the above differences are consistent with our hypotheses and significant at the 1% level based on tests of differences in means. Except for distance, the above differences are also significant at the 1% level based on tests of differences in medians. The covered subsample shows dramatically more involvement by underwriter analysts, reflecting underwriters' tendency to provide coverage of their clients' stocks, as documented by Bradley, Jordan, and Ritter (2003) and Cliff and Denis (2004). We find no significant difference between the covered and non-covered subsamples in analyst general experience, star status or the number of firms covered by the analysts. This is unsurprising, since these variables are primarily traits of analysts. Although they are technically analyst-firm characteristics because we measure them relative to a firm's IPO date, they vary little across firms.

B. Multivariate Analyses

Tables III shows preliminary evidence that analysts' decisions of whether and when to initiate coverage on IPO firms relate to analyst geographic proximity, among other factors. In this section, we provide multivariate analyses of analysts' coverage decisions and, conditional on providing coverage, the timing of the coverage initiation.

Based on Bhushan (1989), we assume that an analyst's decision to initiate coverage of an IPO firm is based on a tradeoff between costs and benefits of following particular firms. The benefits might include, for example, catering to investment needs of existing and potential institutional clients, generating increased commissions for their brokerage firms, or generating investment-banking fees. The costs presumably include the direct costs of acquiring information about new firms, but could include reputational costs if the analyst does a poor job forecasting and providing recommendations about the new firms. We take a pragmatic approach to specifying our model, and rely on the previous literature for factors other than geographic proximity that might affect analysts' coverage decisions.

We study analysts' coverage decisions using a logit model. To study coverage timing, we use both Cox regression and a Tobit model, with the duration of interest starting at the IPO date and ending with either an analyst's coverage initiation or the end of a two-year window, whichever is earlier. In all multivariate models we control for time and industry effects by including IPO-year and industry indicator variables. Based on findings in Gow, Ormazabal, and Taylor (2009), we adjust standard errors for two-way clustering at both the firm and IPO-year level to correct for cross-sectional and time-series dependence. Our regression model takes the following general form:

$$cover\_decision_{aft} = \alpha + \beta_1 local_{aft} + \beta_2 specialist_{aft} + \sum_{i=1}^{K} \delta_i control_{aft}$$
$$+ \sum_{i=2}^{I} \eta_i + \sum_{Y=1996}^{2007} \gamma_Y + \varepsilon_{aft}$$

where the dependent variable is *cover* for the coverage likelihood analysis, and *interval* for the coverage timing analysis. Subscript *a* stands for analyst, *f* for IPO firm, *t* for IPO date, *i* for industry and *Y* for IPO year. We control for firm, analyst, and brokerage characteristics, defined in Table I, that prior research shows to affect analyst coverage decisions. The industry indicators are based on 2-digit SIC codes.

a. Determinants of analyst coverage likelihood

Table IV shows our logit analysis of the impact of geographic proximity on the likelihood of analysts to cover IPO firms within two years after the issue dates. Columns (1) through (4) report the choice sample that is restricted to analysts covering at least five IPO firms. Column (5) reports on analysts working with the largest (in terms of number of sample analysts) 20 brokers, with no restriction on the number of IPOs covered by each analyst. Column (6) reports on all analysts that have covered any of the 3,035 sample IPOs. We do not report coefficients for industry or IPO-year indicators. [INSERT TABLE IV]

Consistent with the previous literature on the determinants of analyst following at the firm level (see Bhushan (1989), O'Brien and Bhushan (1990), Rajan and Servaes (1997), Cliff and Denis (2004), and Bradley, Jordan and Ritter (2008)), Table IV shows that analysts are more likely to cover IPO firms underwritten by their employers, those backed by venture capital, those held by many institutions, those with more underpricing and strong stock performance within the first six months, those with upward pre-IPO price adjustment and those with larger firm size. However, we find more experienced analysts and those with star status are less likely to cover our sample IPOs, perhaps because they prefer more established companies. Percentage holdings by institutional investors are not significant determinants of the coverage decision. The number of other firms followed by the analyst changes sign depending on the sample we use.

Table IV confirms our main hypothesis, that analyst geographic proximity increases the likelihood that an analyst will cover an IPO firm, controlling for other determinants of this decision. In all columns except for column (2) we use the indicator *local* to proxy for geographic proximity between the analyst and firm. The coefficients for *local* are consistently positive and significant. We can interpret the exponential of the logistic regression coefficient as the odds ratio corresponding to a one-unit change in the variable. For example, in column (1) the coefficient of 0.51 on *local* indicates an odds ratio of 1.67, meaning that analysts are 67% more likely to cover IPO firms located in their home states than those in other states. The odds ratio for *specialist* and *underwriter* in that same regression is 15.45 and 8.54, implying that an analyst is 14 times more likely to cover an IPO firm if she covers at least five firms in the same industry than if she is not an industry specialist, and seven times more likely to cover an IPO firm if the analyst's broker was the manager or co-manager of this IPO.

In Column (2) we use *distance_log* to proxy for (the inverse of) geographic proximity between analysts and firms. The negative and significant coefficient on *distance_log* confirm the results reported above, that analysts working near the firm are more likely to initiate coverage. In column (3) we add an interaction term between the *local* and *specialist* indicators to our benchmark model (1). In column (4) we add an interaction term between the *local* and *underwriter* indicators. The coefficient for the two interaction term is significantly negatively, indicating that geographic proximity increases the likelihood of local analyst coverage more for non-specialists and non-underwriter analysts. We reach similar conclusion when we examine subsamples based on a cut on analysts' specialist or underwriting status. [11]

b. Determinants of analyst coverage timing

Because the static logit model fails to account for the timing of analyst coverage, we use both Cox regressions and Tobit regressions to model the duration between an IPO and coverage initiation within two years of the IPO date. Table V shows the results based on Cox regression, or duration analysis, for the coverage sample. It is possible to estimate Cox regressions using the choice sample, with all non-

[11] Buis (2009) provides an intuitive interpretation of additive versus multiplicative interactions in non-linear models using subgroup analysis. In unreported results we tabulate the marginal effects for models (3) and (4) following Buis (2009), which are similar to those in Table II Panel A.

coverage analyst-firm observations treated as "surviving" beyond the end of our two-year window. Recall, however, that the overall coverage rate in the choice sample is only 0.62%. Hence, the non-coverage observations dominate, making this Cox regression effectively equivalent to the likelihood analysis in Table IV. When we restrict attention to the coverage sample, we can observe differences in duration within the two-year window. [INSERT TABLE V]

As in Table IV, columns (1) to (4) of Table V report on analysts covering at least five of our sample IPO firms. Column (5) reports on analysts working with the top 20 brokers, and Column (6) on all analysts that have covered any of our sample IPO firms. For all columns we find positive and significant coefficients on *underwriter, specialist* and *experience*, indicating that underwriter analysts, industry specialist and those with more prior forecasting experience initiate coverage more quickly. The coefficients on *underpricing* and *retmth6* are negative and significant, indicating later coverage initiations for more underpriced firms and those with stronger stock performance six months after IPOs. An alternative interpretation is that these firms may attract later coverage than less underpriced and poorer-performing firms. Other control variables do not contribute significantly to the model.

Table V confirms our hypothesis that geographic proximity accelerates analysts' coverage initiation on IPO, after controlling for other determinants. In column (1) of Table V the odds ratio for *local* is 1.062 (=exp(0.08)), suggesting that an analyst is 6.2% more likely to cover an in-state firm than one from another state at any point in time. In Column (2) we use *distance_log* to proxy for (the inverse of) geographic proximity between analysts and firms. The coefficient on *distance_log* is negative and significant. In column (3) we add an interaction term between the *local* and *specialist* indicators to our benchmark model (1). While the coefficient on *local* is positive, it slightly misses its significance at the 10% level. The coefficient on the interaction term is significantly positive, implying that geographic proximity accelerate analysts' coverage initiations especially for specialists. In column (4) we add an interaction term between the *local* and *underwriter* indicators. The coefficient on this interaction term is significantly negatively, and the sum of local dummy and the interaction term is almost zero, indicating that geographic proximity does not accelerate coverage initiation once the underwriter analysts decide to cover the firms.

We use tobit regression for the determinants of analyst coverage timing in Table VI. One advantage of using tobit regression is that the coefficients indicate the effect of the underlying variables in terms of the number of days after IPO dates. The statistically significant coefficient estimate of -150.14 on *underwriter* in Column (1) implies that analysts affiliated with the IPO underwriter initiate coverage about 150 days earlier than non-underwriter analysts, all else equal. Industry specialists, analysts with longer experience and those covered more firms in the previous year also initiate coverage earlier. The positive and significant coefficients on underpricing, the price adjustment during the IPO process, and return performance in the first six months post-IPO suggest that higher returns delay coverage. A plausible alternative interpretation, as for the similar results in the Cox regression, is that firms with good future prospects attract analysts who did not provide coverage immediately after the IPO, while firms with weaker performance do not. Unlike the Cox regressions, the coefficients on *mktvalue* is positive and significant at the 10% level except for the full coverage sample in Column (6). Star status of analysts and institutional investors do not affect the timing of coverage initiation. [INSERT TABLE VI]

As before, our hypothesis tests concern the measures of geographic proximity, *local* and *distance_log*. Overall we find statistically significant coefficient estimates with the expected sign for both measures of geographic proximity, indicating that analysts cover nearby IPO firms more promptly than distant ones. For example, the coefficient estimate of -14.99 on *local* in Column (1) indicates that analysts initiate coverage on firms within the same state about two weeks earlier than on out-of-state firms. In column (3) we add an interaction term between the *local* and *specialist* indicators to our benchmark model (1). While the coefficient on *local* remain negative and significant, the coefficient on the interaction term is negative but insignificantly, implying that geographic proximity accelerate analysts' coverage initiations both for specialists and non-specialists. In column (4) we add an interaction term between the *local* and *underwriter* indicators. The coefficient on *local* increased to 23.06, indicating that for non-underwriter analysts, geographic proximity as proxied by state boundary accelerates coverage initiations by more than three weeks. The coefficient on this interaction term is significantly negatively, and the sum of local dummy and the interaction term is almost zero, indicating that geographic proximity does not accelerate coverage initiation for the underwriter analysts. In sum, both Table V and VI show that proximate analysts initiate coverage of IPO firms more quickly than distant analysts. However, this effect is overshadowed by the presence of underwriting relationship.

C. The moderating effect of firm and analyst traits

Does the link between geographic proximity and an analyst's propensity to cover an IPO firm vary with the characteristics of the firms and the analysts? Table VII shows whether firm and analyst traits have any effect on the relationship between analysts' geographic proximity and their coverage decisions by adding a proxy for firm / analyst trait and an interaction term between local dummy and the trait based on benchmark models of column (1) in Table IV, V and VI, respectively. Column (1) - (3) are based on logit regression, Column (4) - (6) on Cox regression, and Column (7) - (9) on Tobit regression. For brevity we only report the results on local dummy, firm / analyst traits and their interaction terms. The number of observations for Logit (Cox and Tobit) is 2,356,038 (14,639) except for model (1) and (5), which is 2,004,290 (12,173) and 1,561,827 (9,988), respectively.

The first three variables are meant to capture the complexity of IPO firm operations. The indicator variable *nsegmentg* equals one if an IPO firm has reported operations in at least two geographic locations (sample median); *nsegment* equals one if an IPO firm has reported at least two business segments(sample median); *diversification* is the weighted average ratio of each segment sales to the total sales of an IPO firm in the first annual report following the IPO, with the weight for each segment being the logarithm of the inverse of its ratio. We obtain segment-level sales from the Compustat segment file. We find that the coefficients on *local* remain significant, and none of the coefficients on the interaction term is significant in Column (1) - (9). This suggest that none of these proxies for the operation complexity affects the impact of geographic proximity on analysts' propensity to cover IPOs.

We then look at other firm characteristics that proxy for the information environment of IPO firms. *big* is a dummy equal to one if the market value of an IPO is greater than the sample median;

retstddum is a dummy equal to one if the daily return volatility of an IPO firm is greater than the sample median; *insthld* is the average holdings of shares outstanding of an IPO firm by institutional investors in the IPO year; *uniqueness* is a dummy equal to one if the SIC code of the IPO firm is between 3400 and 4000, which is meant to capture the uniqueness of the IPO firms' products and services following Frank and Goyal (2009). The coefficients on *local* remain significantly positive for logit and cox regressions and significantly negative for tobit regression. For the logit regressions in Column (1) - (3), the interaction terms of *local* with *big* and *insthld* are negative and significant, while the interaction terms of local with *retstddum* and *uniqueness* are positive and significant, suggesting that the effect of geographic proximity on the likelihood of analyst coverage is especially prominent for smaller firms, firms with more uncertainty, firms with less institutional involvement and those produce more unique products. For cox regressions, the interaction terms for *big*, *insthld,* and *uniqueness* are significant, while for tobit regressions the interaction terms for *big* and *insthld* are significant. These results imply that geographic proximity increase the likelihood and promptness of coverage initiations for smaller firms, firms with less institutional involvement and those produce more unique products. IPO underpricing does not affect the impact of geographic proximity on analysts' coverage decisions.

In row (9) to (10) we examine the impact of analyst traits in terms of their previous star status and general forecast experience. The coefficients on the interactions terms for *star* and *experience* are negative, but significant only for *experience* in the logit and tobit regressions. In the cox regression the coefficients on both interactions terms are positive and significant. These results suggest that analysts' prestige to a certain degree moderate the effect of geographic proximity in their decision to cover IPOs, but accelerate their coverage initiations once they decide to follow these firms. [INSERT TABLE VII]

IV. Does local analyst coverage matter?

So far we have documented strong evidence that geographic proximity facilitate analysts' coverage of IPO firms. An interesting issue is whether this influence of geographic proximity on analyst coverage decisions has real effects for the underlying firms. Since previous studies have shown that the number of analyst following is positively related to firm value, one channel for local analyst coverage to affect the firm value of the target IPOs is to bring along other analysts who would otherwise have neglected these firms.

We classify our sample US IPO firms into four groups based on the status of analyst coverage within half a year immediately after the IPO dates: firms not covered by any analysts (N), those covered exclusively by local analyst who domicile in the same state as that of the underlying firms (L), those covered exclusively by non-local analyst (F), and those covered by both local and non-local analysts (B). Table VIII shows the comparison of firm characteristics for these four firm groups. The first four columns show the mean value for each firm characteristic across the firms within each group. The Difference columns report the p-values in parentheses from t-tests of differences in means. The last row in the table shows the number of firms for each of the four groups.

Table VIII shows that IPOs covered by both local and non-local analysts (B group) in the first half year after the IPO dates are the biggest, have the highest Pre-IPO filing price adjustment and post-IPO stock performance, and are most visible to venture capital firms and institutional investors. The non-covered group and local only group are generally smaller, has negative post-IPO stock performance and are less visible to venture capital firms and institutional investors. The *t*-test indicates that there is no significant difference between the non-covered group and local only group, which motivates us to use these two groups of firms to examine whether local analyst coverage attracts coverage initiations from other analysts. [INSERT TABLE VIII]

We keep IPO firms that are either covered exclusively by local analysts or not covered by any analysts within half a year immediately after the IPO date, and then track these firms for coverage by three groups of analysts within the next one year: all analysts, non-local analysts, and local analysts. We create a dummy variable *localonly* that equals one if a firm belongs to the local analyst only group, zero if the firm belongs to the group that is not covered by any analysts. Table XI shows the impact of local analyst coverage. We use a logit model in Panel A, with the dependent variable *cover* being a dummy that equals one if a firm is covered by any analysts belonging to the analyst group in concern within one year after the first six months of IPO dates, and zero otherwise. In Panel B, the dependent variable *following* is the number of analysts from each analyst group that initiate coverage on the underlying firms. We assign a value of zero if there is no analyst coverage. Following Rock, Sedo, and Willenborg (2001) and Bae, Tan and Welker (2008), we use negative binomial regressions for the determinants of analyst following. [INSERT TABLE IX]

Column (1) to (3) are based on analyst following for all analysts, non-local analysts, and local analysts, respectively, that initiate coverage within one year after the first six months of IPO dates. We find that overall, *localonly* is significantly positive for both the logit regressions in Panel A and negative binomial regressions in Panel B, suggesting that among the IPO firms that are not covered by any analyst or covered only by local analysts, the presence of local analysts help attract other analysts to cover the firms. For example, the odds ratio for the *localonly* in column (1) Panel A is 7.69, implying that relative to the firms not covered by any analyst, firms covered by local analysts during the initial period are at least six times more likely to be covered by other analysts within the next one year. The odds ratio for the *localonly* in column (2) is 2.34, implying that firms covered by local analysts during the initial period are 134% more likely to be covered by some non-local analysts within the next one year relative to the firms not covered by any analysts. Our results are qualitatively the same when we set the initial period to one year (Column (4) - (6)). These results suggest that prompt coverage by local analysts post IPO date attracts other analysts to jump into the boat and thus increase the visibility of the IPOs to the investors.

V. Robustness checks

In the above sections we show that geographic proximity increases analysts' coverage likelihood and accelerates their coverage initiation once they choose to cover. These main results are robust to various changes in the samples, regression models, and alternative proxies for analyst geographic proximity. We have identified some of these alternatives previously in footnotes, and explain others in more detail below.

A. Sub-period analysis

Advances in technology may act to reduce the importance of geographic proximity. We explore this via changes through time, by examining whether the effect of analyst geographic proximity has changed over our sample period. We divide our sample into early and late periods, based on whether the IPO occurred before the end of year 2000 (alternatively, 1999), or after. We run the benchmark model (1) from Tables IV, V and VI separately for the early and late periods. In unreported results we find qualitatively similar logit results to those in Table IV, with the coefficient on *local* statistically significant at the 1% level. However, the odds ratio for *local* declines from the early to late period, suggesting that its impact, while still significant, may have diminished over time. In the Tobit and Cox regressions, we find lower coefficients on *local* in the later sub-period than in the early one, and in fact the coefficient on *local* lacks statistical significance in the later sub-period. This suggests that geographic proximity has become less important to the timing of analysts' coverage in recent years.

B. Alternative samples

For both coverage sample and choice sample, we find that our main results are robust to using the following samples. A) We exclude unit offerings, American Depository Receipts, foreign corporations (F-1 filings), real estate investment trusts, mutual funds, financial institutions (SIC code between 6000 and 6999) and service companies (SIC code greater than 8100); B) We exclude analysts in New York City, where more than 40% of our sample analysts are located; C) We exclude firms located around Silicon Valley in Northern California; D) We restrict the time frame for coverage to within one year instead of two years post-IPO. E) For the logit regression based on the choice sample, we include IPO firms that are not covered by our sample analysts. F) We delete 32 IPOs with offer price per share less than five US dollars.

C. Alternative regression specifications

In all the multivariate regressions except for Table IX, we adjust standard errors for two-way clustering at both the firm and year levels. The main results do not change when we adjust standard errors for clustering at the analyst, brokerage, IPO issue year, or state level. For the coverage likelihood analysis we obtain similar results when we use probit regressions. For the coverage timing analysis, our results do not change when we use OLS with log-transformed days as the dependent variable.

D. Alternative control variables

We have used an indicator variable *specialist* to proxy for analysts' industry knowledge in the target firms. Alternatively we compute analysts' industry expertise based on segment-level sales obtained from the Compustat Segment file. SFAS Nos. 14 and 131, and SEC Regulation S-K require U.S. firms to report financial data for business segments whose revenues, assets, or profits exceed 10% of corresponding totals for the consolidated firm. For each reportable business segment, Compustat reports segment assets, sales, operating income before depreciation, and capital expenditures, along with the primary and secondary NAICS and SIC code of the segment.[12] We compute industry expertise for each analyst-firm pair as follows. For each firm-year we compute the ratio of segment sales, identified by 3-digit NAICS subsector, to the firm's total sales. We merge the Compustat segment sales data with analyst coverage information to compute, for each analyst-year, the ratio of sales within each subsector to the total sales of all the firms covered by the analyst that year. An analyst's industry expertise in a particular firm is the sum across subsectors for the firm-year of the product of Sales_firm with Sales_analyst. We also measure analysts' industry expertise based on the number of firms the analyst follows in each 2-digit SIC industry or Fama-French 48 industry prior to the IPO date. Our results do not change when we substitute *specialist* for any of these alternative proxies for analysts' industry knowledge.

VI. Conclusion

Despite abundant evidence regarding the impact of analyst coverage on target firms and analysts' employers, we have an incomplete understanding of the factors that motivate an individual analyst's coverage decision. Consistent with the idea that analyst-firm alignment matters for the analyst's coverage decision, we provide a key dimension of such an alignment: analysts' geographic proximity to target firms. We find that proximity increases the likelihood that an analyst will initiate coverage of IPO firms. The logit regression shows that analysts are 67% more likely to cover IPO firms headquartered in their

[12] NAICS employs a 6-digit coding system where the first two digits designate the sector, the third digit designates the subsector, the fourth digit designates the group, the fifth digit represents the NAICS industry, and the sixth digit designates the individual country-level national industries. NAICS contains 20 sectors, 96 subsectors, 311 groups and 721 industries. Our coverage sample includes 93 subsectors.

home states than those in other states. Geographic proximity matters most for non-underwriter analysts and those with less industry expertise.

We also find that geographic proximity accelerates analysts' coverage initiation on IPO firms. Geographic proximity relate negatively and significantly to the time interval between IPO and analyst coverage initiation. Further analyses show that the effect of geographic proximity on analysts' coverage likelihood and promptness is more prominent for smaller firms, firms with less institutional involvement and those produce more unique products. Analysts' prestige to a certain degree moderate the effect of geographic proximity in their decision to cover IPOs, but accelerate their coverage initiations once they decide to follow these firms. Our results are robust to various samples and model specifications.

Among the IPO firms that are not covered by any analyst or covered exclusively by local analysts within an initial period of half a year immediately after the IPO date, the presence of local analysts helps attract other analysts to cover the firms within the next one year, serving as a leap toe to increased visibility of the IPO firms. Prompt local analyst coverage also attracts more other analysts to cover the underlying firms. Our results are qualitatively the same when we set the initial period to one year.

We find that geographic proximity helps determine how much analyst coverage an IPO firm receives in its early stage at which the coverage would be needed most. While we find it plausible that some individual analysts decide whether or not to cover a particular IPO firm, in some cases research firms may strategically allocate analysts to cover particular firms, or IPO firms may seek coverage from certain analysts.[13] In these cases, our results suggest that analyst proximity affects their employers' allocation decisions, or that IPO firms preferentially seek coverage from nearby analysts. In any of these interpretations, our factors of geographic proximity affect IPO coverage.

[13] The popular press suggests that analysts pick and choose IPO firms. See Finegan, Useem, and Mamis (1996).

REFERENCES

Bae, K-H., H. Tan, and M. Welker. 2008. International GAAP differences: The impact on foreign analysts, *The Accounting Review 83 (3)*, 593-628.

Bae, K-H., R. M. Stulz, and H. Tan. 2008. Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts, *Journal of Financial Economics* 88, 581–606.

Barth, M., R. Kasznik, and M. McNichols. 2001. Analyst coverage and intangible assets, *Journal of Accounting Research* 39, 1-34.

Best, R. W., J. D. Payne, and J. C. Howell. 2003. Analyst following and equity offerings subsequent to IPOs, *Review of Quantitative Finance and Accounting* 20, 155-168.

Bhushan, R. 1989. Firm characteristics and analyst following, *Journal of Accounting and Economics* 11, 255-274.

Botosan, C., and M. Harris. (2000). The Cross-sectional determinants of disclosure timeliness: an examination of quarterly segment disclosures, *Journal of Accounting Research*, 524-554.

Bradley, D.J., B.D. Jordan, and J.R. Ritter. 2003. The quiet period goes out with a bang, *Journal of Finance* 58, 1-36.

Bradley, D.J., B.D. Jordan, and J.R. Ritter. 2008. Analyst behavior following IPOs: the "bubble period" evidence, *Review of Financial Studies* 21, 101-133.

Buis, Maarten L., 2009, Simple interpretation of interactions in non-linear models, *The Stata Journal* 10 (2), 1-4.

Brennan, M.J., Jegadeesh, N., Swaminathan, B. 1993. Investment analysis and the adjustment of stock prices to common information. *Review of Financial Studies* 6: 799-824.

Butler, A., 2008, Distance Still Matters: Evidence from municipal bond underwriting, *Review of Financial Studies* 21, 763-784.

Chang, C., 2003. Information footholds: expatriate analysts in an emerging market. Unpublished working paper. Haas School of Business, U. C. Berkeley.

Chang, X., S. Dasgupta, and H. Hilary. 2006. Analyst coverage and financing decisions, *Journal of Finance* 61, 3009-3048.

Cliff, M.T. and D.J. Denis. 2004. Do initial public offering firms purchase analyst coverage with underpricing? *Journal of Finance* 59, 2871–2901.

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.

Cooper R., T. Day & C. Lewis. 2001. Following the leader: A study of individual analysts' earnings forecasts, *Journal of Financial Economics*, 61, 383-416.

Coval, J. D., and T. J. Moskowitz, 1999. Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

Coval, J. D., and T. J. Moskowitz, 2001. The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 4, 811–841.

Das, S., R. Guo, and H. Zhang. 2006. Analysts' selective coverage and subsequent performance of newly public firms, *Journal of Finance* 61, 1159-1185.

Derrien, Francois. 2006. Currying favor to win IPO mandates, Working paper, HEC Paris.

Finegan, Jay, Jerry Useem, and Robert A. Mamis, 1996. No tech, no takers, *Inc*. 18, 44–49.

Gilson, S., P. Healy, C. Noe, and K. Palepu. 2001. Analyst specialization and conglomerate stock breakups, *Journal of Accounting Research* 39, 565–582.

Financial Accounting Standards Board (FASB). 1976. Financial reporting for segments of a business enterprise. *Statement of Financial Accounting Standards No. 14*. Norwalk, CT: FASB. <http://www.fasb.org/jsp/FASB/Page/PreCodSectionPage&cid=1218220137031>, accessed 25 May 2010.

Financial Accounting Standards Board (FASB). 1997. Disclosures about segments of an enterprise and related information. *Statement of Financial Accounting Standards No. 131*. Norwalk, CT: FASB. <http://www.fasb.org/jsp/FASB/Page/PreCodSectionPage&cid=1218220137031>, accessed 25 May 2010.

Frank, Murray Z. and Vidhan K. Goyal, 2009. Capital Structure Decisions: Which factors are reliably important? Financial Management, 1-37.

Gow, I.D., G. Ormazabal, and D.J. Taylor. 2009. Correcting for cross-sectional and time-series dependence in accounting research, *The Accounting Review*, forthcoming.

Hope, O-K. 2003. Analyst following and the influence of disclosure components, IPOs and ownership concentration, *Asia-Pacific Journal of Accounting and Economics* 10 (2).

Irvine, P.J. 2001. Do analysts generate trade for their firms? Evidence from the Toronto Stock Exchange, *Journal of Accounting and Economics* 30, 209-226.

Irvine, P.J. 2003. The incremental impact of analyst initiation of coverage, *Journal of Corporate Finance* 9, 431-451.

Ivkovic, Z., and S. Weisbenner, 2005. Local does as local is: information content of the geography of individual investors' common stock investments, *Journal of Finance* 60, 267-306.

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

Jacob, T., T. Lys, and M. Neale. 1999. Expertise in forecasting performance of security analysts, *Journal of Accounting and Economics* 28, 51-82.

James, C, and J. Karceski. 2006. Strength of analyst coverage following IPOs, *Journal of financial Economics* 82, 1-34.

Kadan, O., L. Madureira, R. Wang, and T. Zach. 2009. Conflicts of Interest and Stock Recommendations: The Effects of the Global Settlement and Related Regulations, *Review of Financial Studies* 22, 4189-4217.

Kirk, Marcus. 2010. Research for sale: Determinants and consequences of paid-for analyst research, *Journal of financial Economics,* forthcoming.

Kedia, S. and Zhou. Z., 2007, Local Market Makers and Trading Costs, Working Paper, Rutgers University.

Krigman, L., W.H. Shaw, and K.L. Womack. 2001. Why do firms switch underwriters? *Journal of Financial Economics* 60, 245-284.

Lang, M. H., K. V. Lins, and D. P. Miller. 2004. Concentrated control, analyst following, and valuation: Do analyst matter most when investors are protected least? *Journal of Accounting Research* 42: 589-623.

Li, Y., P.R. Rau, and J. Xu. 2009. The five stages of analyst careers: Coverage choices and changing influence, Working paper, Purdue University.

Liang, L., E.J. Riedl, and R. Venkataraman. 2008. The determinants of analyst-firm pairings, *Journal of Accounting and Public Policy* 27, 277-294.

Malloy, C. 2005. The geography of equity analysis, *Journal of Finance* 60, 719-755.

McNichols, M., and P. O’Brien. 1997. Self-selection and analyst coverage, *Journal of Accounting Research* 35, 167-199.

McNichols, M., and P. O’Brien. 2001. Inertia and discreteness: Issues in modeling analyst coverage, Working paper, University of Waterloo.

McNichols, M., P. O’Brien, and O. Pamukcu. 2007. Unaffiliated analysts’ recommendation performance for IPO firms, Working paper, University of Waterloo.

Mozes, H.A. 2003. Accuracy, usefulness and the evaluation of analysts’ forecasts, *International Journal of Forecasting* 19, 417-434.

Niehaus, G., and D. Zhang. 2008. The impact of sell-side analyst research coverage on an affiliated broker's market share of trading volume, Working paper, University of South Carolina.

O’Brien, P. and R. Bhushan. 1990. Analyst following and institutional ownership, *Journal of Accounting Research*, 28, 55-76.

O'Brien, P.C., M.F. McNichols, and H-W. Lin. 2005. Analyst impartiality and investment banking relationships, *Journal of Accounting Research* 43, 623-650.

Previts, G., and R. Bricker. 1994. A content analysis of sell-side financial analyst company reports, *Accounting Horizons* 8, 55-70.

Rajan, R.G., and H. Servaes.1997. Analyst following of initial public offerings, *Journal of Finance* 52, 507–529.

Ramnath, S., S. Rock, and P. Shane. 2008. The financial analyst forecast literature: A taxonomy with suggestions for future research, *International Journal of Forecasting* 24, 34-75.

Rock, S., S. Sedo, and M. Willenborg. 2001. Analyst following and count-data econometrics, *Journal of Accounting and Economics* 30, 351-373.

Rogers, R., and J. Grant. 1997. Content analysis of information cited in reports of sell-side financial analysts, *Journal of Financial Statement Analysis* 3, 17-30.

Roulstone, D. 2003. Analyst following and market liquidity, *Contemporary Accounting Research* 20 (3). 551-578.

Seasholes, M., and Ning Zhu. 2009. Individual Investors and Local Bias, *Journal of Finance,* forthcoming.

U.S. Securities and Exchange Commission (SEC). 2010. *Regulation S-K* [17 CFR Part 229]. http://www.sec.gov/divisions/corpfin/ecfrlinks.shtml, accessed 25 May 2010.

Shultz, P. 2003. Who makes markets, Journal of Financial Markets 6. 49-72.

Uysal, V.B., S. Kedia, and V. Panchapagesan, 2008, Geography and acquirer returns, *Journal of Financial Intermediation* 17, 256-275.

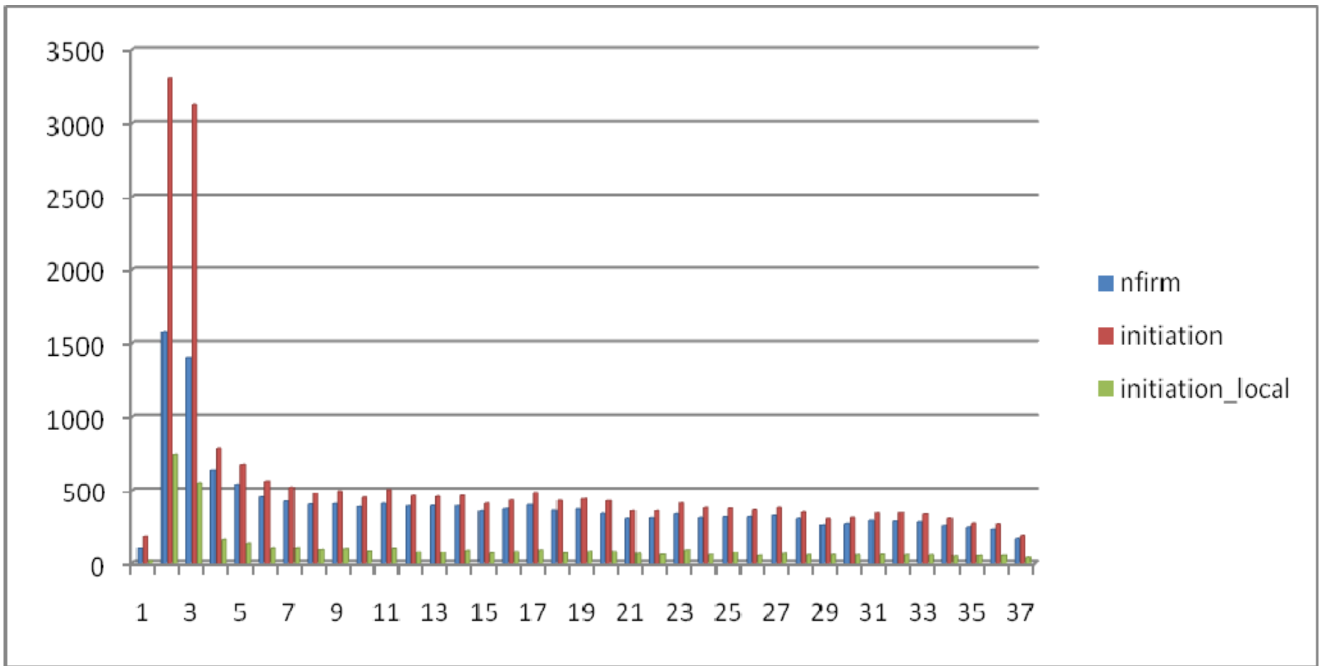
Yu, F. 2008. Analyst coverage and earnings management, *Journal of Financial Economics* 88, 245-271.

Tehranian, H, Zhao, M., and J. Zhu. 2010. Can analysts analyze mergers, Working paper, Boston College.

Pirinsky C. A., and Q. Wang. 2010. Geographic Location and Corporate Finance: A Review, Handbook of Emerging Issues in Corporate Governance, World Scientific Publishing, Forthcoming.

Figure 1
The timing of analyst coverage initiations on IPO firms

This figure shows the number of IPO firms with analyst coverage initiations by distinct analysts and the number of analyst coverage initiations by all analysts or by local analysts during each period of 20 days after IPO date. For each firm within two year post IPO date, we keep only the first earnings forecast for each analyst that are identified with geographic locations based on the Nelson's Directory of Investment Research. There are a total of 20,715 initiations by 4,459 analysts on 3,035 IPO deals during 1996 to 2009.



Appendix A
Sample selection

Criteria	Number of IPOs	Number of analysts
US IPOs from Thomson One Banker during 1996-2010 with non-missing offer price and midpoint of the initial filing range	4,129	
Subtract firms:		
Without match to I/B/E/S	287	
Without return information from CRSP	97	
With analyst coverage within 3 years before IPO date (recent privatizations)	37	
Missing latitude and longitude information of IPO firms	12	
IPOs not covered within two years post IPO dates by sample analysts with non-missing geographic locations	661	
IPOs covered by sample analysts with non-missing geographic locations	3,035	4,459
Subset with analysts covering at least 5 sample IPOs	2,857	1,538

Appendix B
Top 20 brokerages

This appendix lists the Top 20 brokerages in terms of the number of analysts with non-missing geographic information that have covered any of our sample firms within two years post-IPO dates. The number of analysts or firms covered by each research firm does not add up to the total, because analysts cover multiple firms, and multiple analysts can cover a given firm.

	Research firm	No. of IPO analysts	No. of IPO firms covered
1	Credit Suisse First Boston	190	657
2	Banc of America Securities LLC	154	633
3	Citigroup	183	595
4	Merrill Lynch	198	542
5	Deutsche Bank North America	147	536
6	Lehman Brothers	129	535
7	Piper Jaffray	97	534
8	Goldman Sachs & Co.	158	517
9	Robertson Stephens	79	488
10	Morgan Stanley	151	480
11	UBS	158	467
12	J.P. Morgan	149	448
13	Bear, Stearns & Co.	122	421
14	CIBC World Markets Corp.	115	417
15	Wachovia Securities	102	414
16	Prudential Equity Group, LLC	110	377
17	RBC Capital Markets	92	371
18	Thomas Weisel Partners	72	357
19	Jefferies & Co.	72	290
20	A. G. Edwards & Sons, Inc.	80	227
	All other research firms	2,489	2,747
	Total	4,459	3,035

Table I
Variable description

This table describes our dependent and independent variables. The data source is Thomson One unless specified otherwise. Variables subscripted with *af* (*f*) are measured by analyst-firm (firm).

Variable	Description and data sources
$cover_{af}$	Indicator variable equal to one if an analyst covers a firm, zero otherwise.
$interval_{af}$	Time interval in days between IPO issue date and an analyst's first earnings forecast of the firm.
$local_{af}$	Indicator variable equal to one if an analyst is located in the same state as the firm, zero otherwise. Analyst locations are from annual volumes of Nelson's Directory of Investment Research for 1997-2009, while firm headquarter locations are from Thomson One Banker.
$distance\_log_{af}$	Natural log of geographic distance in kilometers between analyst and firm headquarters based on latitudes and longitudes of their city locations. The data sources are the same as for *local*.
$specialist_{af}$	Indicator variable equal to one if the analyst covers at least five firms in the same I/B/E/S industry as the given firm in the year prior to firm's IPO date, zero otherwise. We compute this variable based on the I/B/E/S detail file.
$underwriter_{af}$	Indicator variable equal to one if an analyst's employer is a manager or co-manager of IPO.
$ventureback_{f}$	Indicator variable equal to one if venture capital is present at the IPO date, zero otherwise.
$numinst_{f}$	Average number of institutional investors based on quarterly CDA/Spectrum 13f Holdings in the IPO year. This variable is in natural log form in the multivariate regressions.
$insthld_{f}$	Average holdings of shares outstanding of an IPO firm by institutional investors based on quarterly CDA/Spectrum Institutional Money Manager (13f) Holdings in the IPO year.
$underpricing_{f}$	IPO first-day return calculated as the difference between the first trading day closing price and offer price, scaled by the offer price.
$retmth6_{f}$	Cumulative return during the first 6 months after the IPO date, based on CRSP daily return.
$priceadj_{f}$	Difference between the offer price and the midpoint of the initial filing range for the IPO, scaled by the midpoint of the initial filing range.
$mktvalue_{f}$	Market value pro forma offer at IPO date, denominated in million U.S. dollars. We use the natural log form of this variable in the multivariate regressions.
$experience_{af}$	Time interval in years between an analyst's first forecast in the I/B/E/S database and the firm's IPO date. We use I/B/E/S detail data.
$ntik_{af}$	Number of firms an analyst covers in the year prior to the firm's IPO date. We use I/B/E/S detail data. We use the natural log form of this variable in the multivariate regressions.
$star_{af}$	Indicator variable equal to one if an analyst is a star analyst, according to Nelson's Directory of Investment Research, in the year prior to the firm's IPO date.
$nsegmentg_{f}$	Indicator variable equal to one if an IPO firm has reported operations in at least two geographic locations (sample median).
$nsegment_{f}$	Indicator variable equal to one if an IPO firm has reported at least two business segments(sample median).
$diversification_{f}$	Weighted average ratio of each segment sales to total sales of an IPO firm in the first annual report following the IPO, with the weight for each segment being the logarithm of the inverse of its ratio. We obtain segment-level sales from the Compustat segment file.
$retstddum_{f}$	Indicator variable equal to one if daily return volatility is greater than the sample median.
$uniqueness_{f}$	Indicator variable equal to one if the SIC code of the IPO firm is between 3400 and 4000 (firms producing computers, semiconductors, chemicals, and allied, aircraft, guided missiles, and space vehicles and other sensitive industries).

Table II
Distributions of IPO firms and analysts

This table shows the distribution of IPO firms and analysts by year. There are 3,696 US IPOs during 1996-2009, with 3,035 IPOs being covered by 4,459 analysts that we could identify their geographic locations based on the Nelsons' Directory of Investment Research. They provide a total of 20,715 one-year-ahead earnings coverage initiations within two years after the IPO date. Panel A shows the distribution and summary statistics of IPO firms and analysts by year. No. of IPOs is the total number of IPOs during 1996-2009, which totals 3,696. The number of covered IPOs and analysts are the number of IPOs and analysts in the full coverage sample, respectively. Matching rate is the proportion of I/B/E/S analysts found in Nelson's Directory with non-missing locations. The numbers in Columns (5)-(9) are averages across IPO firms within a given IPO year. Table I defines the variables for these columns. The Average reported at the bottom of each column is the mean across years of the annual average values. Panel B shows the number of analysts and IPO firms located in each state based on the subset of our coverage sample used in our main analyses, 2,857 IPOs and 1,538 distinct analysts covering at least 5 IPOs. The columns labeled Percent show the proportion of this coverage sample represented by that state. In panel B an analyst will be double-counted if she has changed her state location.

Panel A
Distribution and summary statistics by IPO year

Year	No. of IPOs	Covered IPOs	No. of analysts	Match rate	market value	under-pricing (%)	priceadj (%)	retmth6 (%)	venture-back
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1996	711	617	1,450	0.85	300	18.38	0.03	-0.64	0.38
1997	492	424	1,340	0.89	231	14.10	-1.79	13.81	0.27
1998	324	270	1,143	0.91	460	21.51	-0.39	-7.89	0.24
1999	476	441	1,486	0.90	959	64.46	17.27	27.59	0.56
2000	345	328	1,252	0.90	1,212	54.36	11.43	-31.92	0.68
2001	118	77	543	0.89	965	7.56	-1.85	-8.82	0.31
2002	149	69	523	0.92	567	4.39	-2.39	-3.16	0.15
2003	112	72	443	0.90	557	6.94	2.61	5.29	0.24
2004	255	206	1,060	0.84	616	9.00	-5.02	6.25	0.38
2005	221	174	789	0.75	524	7.19	-3.65	7.08	0.19
2006	204	169	740	0.67	573	10.05	-3.30	4.60	0.26
2007	243	159	657	0.65	572	8.05	0.05	-9.00	0.23
2008	35	25	171	0.63	1,257	3.33	-7.39	-17.81	0.09
2009	11	4	18	0.82	152	2.12	-7.02	6.62	0.18
Total / average	3,696	3,035	4,459	0.82	639	16.53	-0.10	-0.57	0.30

Table II (continued)

Panel B
Number of analysts and IPO firms by US state

	State	Analysts		IPO firms	
		Number	Percent	Number	Percent
1	California	343	18.93	770	26.95
2	Texas	52	2.87	265	9.28
3	New York	767	42.33	228	7.98
4	Massachusetts	86	4.75	194	6.79
5	Florida	35	1.93	126	4.41
6	Illinois	78	4.30	108	3.78
7	Pennsylvania	19	1.05	98	3.43
8	Virginia	51	2.81	96	3.36
9	Colorado	15	0.83	86	3.01
10	New Jersey	7	0.39	80	2.80
11	Georgia	29	1.60	77	2.70
12	Washington	10	0.55	69	2.42
13	Minnesota	80	4.42	64	2.24
14	Connecticut	22	1.21	60	2.10
15	Maryland	44	2.43	60	2.10
16	Ohio	9	0.50	47	1.65
17	North Carolina	1	0.06	40	1.40
18	Michigan	2	0.11	39	1.37
19	Tennessee	38	2.10	32	1.12
20	Arizona	0	0	30	1.05
21	Oklahoma	0	0	25	0.88
22	Oregon	22	1.21	25	0.88
23	Indiana	0	0	24	0.84
24	Missouri	26	1.43	22	0.77
25	Utah	0	0	18	0.63
26	Wisconsin	17	0.94	17	0.60
27	Kansas	0	0	16	0.56
28	District of Columbia	9	0.50	15	0.53
29	Nevada	0	.	15	0.53
30	Louisiana	11	0.61	14	0.49
31	Iowa	0	0	13	0.46
32	Kentucky	2	0.11	10	0.35
33	New Hampshire	0	0	9	0.32
34	Alabama	0	0	8	0.28
35	South Carolina	0	0	8	0.28
36	Nebraska	0	0	7	0.25
37	Arkansas	11	0.61	5	0.18
38	Delaware	0	0	5	0.18
39	Idaho	0	0	5	0.18
40	Maine	0	0	4	0.14
	All other	1	1.43	23	0.81
	Total	1,538	100.00	2,857	100.00

Table III
Comparison between subsamples

This table shows comparisons between subsamples. Panel A compares analyst-firm level variables of the covered versus non-covered observations for the choice sample, which contains 2,356,038 analyst-firm pairs, of which 14,639 represent covered observations. We first compute the mean for each analyst across firms in that analyst's covered and non-covered subsets, and then compute the mean and median across analysts for covered and non-covered observations. Pane B reports the average coverage ratio for the choice sample, while Panel B reports the average days to initiate coverage on IPO firms for the coverage sample within each analyst groups. Panel A and B are for the choice sample that contains 2,857 IPOs covered by 1,538 analysts each of whom has covered at least 5 sample IPOs during 1996-2009. Panel C are for the coverage sample that contains 3,035 IPOs covered by 4,459 analysts. We report in parentheses the p-values of difference adjusted for firm-level clustering. All the variables are defined in Table I.

Panel A
Mean analyst coverage ratio by analysts group for the choice sample

	Local (A)	Non- Local (B)	Difference (A)-(B)	P-value of difference
Specialist (a)	7.43	4.96	2.47	(0.00)
Non-Specialist (b)	0.77	0.34	0.43	(0.00)
Difference (a)-(b)	6.66	4.62	2.04	(0.00)
P-value of difference	(0.00)	(0.00)	(0.00)	
Underwriter (a)	4.83	3.17	1.66	(0.00)
Non-Underwriter (b)	0.86	0.38	0.48	(0.00)
Difference (a)-(b)	3.98	2.79	1.18	(0.00)
P-value of difference	(0.00)	(0.00)	(0.00)	

Panel B
Average days to initiate coverage on IPO firms by analyst group for the coverage sample

	Local (A)	Non- Local (B)	Difference (A)-(B)	P-value of difference
Specialist (a)	165	179	-15	(0.00)
Non-Specialist (b)	267	277	-10	(0.10)
Difference (a)-(b)	-102	-98	-5	(0.53)
P-value of difference	(0.00)	(0.00)	(0.53)	
Underwriter (a)	128	124	5	(0.46)
Non-Underwriter (b)	276	296	-20	(0.00)
Difference (a)-(b)	-148	-173	25	(0.00)
P-value of difference	(0.00)	(0.00)	(0.00)	

Panel C
Covered versus non-covered subsamples in the choice sample

Analyst-firm level variables	Mean			Median		
	Non-covered	Covered	Difference p-value	Non-covered	Covered	Difference p-value
	(A)	(B)	(B)-(A)	(C)	(D)	(D)-(C)
local	0.11	0.20	(0.00)	0.08	0.12	(0.00)
distance	1,305	1,126	(0.00)	1,275	1,093	(0.28)
expertise	0.07	0.42	(0.00)	0.06	0.36	(0.00)
specialist	0.04	0.38	(0.00)	0.03	0.38	(0.00)
underwriter	0.06	0.34	(0.00)	0.04	0.28	(0.00)
experience	5.14	5.11	(0.85)	3.76	3.50	(0.70)
star	0.10	0.10	(0.99)	0.00	0.00	(0.35)
ntik	13.07	12.87	(0.43)	12.01	11.86	(0.96)

Table IV
Determinants of analyst coverage likelihood

The table shows the impact of analysts' geographic proximity on their decision to cover an IPO firm. The dependent variable is an indicator equal to one if an analyst covers the firm within two years after its IPO date, and zero otherwise. Our sample IPOs fall within 1996 – 2009. The sample is the choice sample of analyst-firm observations, limited to analysts who cover at least one sample IPO and are active within the first six months following a given firm's IPO. Columns (1) to (4) include analysts who cover at least five sample IPOs. Column (5) reports on analysts working with the Top 20 brokers in terms of number of sample analysts. Column (6) reports on the full choice sample. All models are estimated with logit regression. We define the variables in Table I. The models include industry and IPO-year indicators, though we do not report the coefficients. We report robust z-statistics adjusted for two-way clustering at both firm and year level in parentheses. Panel B reports the marginal effects from models (1), (3), and (4) of Panel A. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
local	0.51***		0.66***	0.63***	0.39***	0.63***
	(7.69)		(11.39)	(9.68)	(4.20)	(10.31)
distance_log		-0.08***				
		(-8.76)				
local*specialist			-0.39***			
			(-8.26)			
local*underwriter				-0.36***		
				(-3.94)		
specialist	2.74***	2.75***	2.81***	2.74***	3.22***	3.02***
	(15.11)	(15.37)	(15.81)	(15.13)	(20.70)	(22.04)
underwriter	2.14***	2.14***	2.14***	2.22***	2.04***	2.16***
	(23.11)	(22.99)	(23.08)	(23.04)	(18.89)	(24.96)
ventureback	0.10**	0.12***	0.10**	0.10**	0.02	0.07*
	(2.24)	(2.58)	(2.25)	(2.24)	(0.60)	(1.66)
numinst	0.08*	0.08**	0.08*	0.08*	0.07***	0.13***
	(1.90)	(2.10)	(1.95)	(1.92)	(2.67)	(3.56)
insthld	-0.04	-0.07	-0.04	-0.04	0.03	-0.04
	(-0.31)	(-0.53)	(-0.32)	(-0.31)	(0.23)	(-0.46)
underpricing	0.17***	0.18***	0.17***	0.17***	0.16***	0.14***
	(3.44)	(3.51)	(3.42)	(3.48)	(3.87)	(2.78)
retmth6	0.26***	0.27***	0.26***	0.26***	0.24***	0.26***
	(13.21)	(13.33)	(13.33)	(13.30)	(7.46)	(11.28)
priceadj	0.29***	0.30***	0.29***	0.28***	0.17***	0.22***
	(4.47)	(4.42)	(4.47)	(4.57)	(3.53)	(4.18)
mktvalue	0.14***	0.14***	0.14***	0.14***	0.16***	0.15***
	(5.58)	(5.57)	(5.61)	(5.52)	(9.62)	(5.94)
experience	-0.46***	-0.47***	-0.46***	-0.46***	-0.50***	-0.53***
	(-15.83)	(-15.88)	(-16.07)	(-15.94)	(-10.34)	(-14.82)
ntik	-0.09***	-0.09***	-0.09***	-0.09***	0.03**	-0.03**
	(-3.99)	(-3.92)	(-4.06)	(-4.00)	(2.35)	(-2.21)
star	-0.23**	-0.25***	-0.23**	-0.24***	-0.15	-0.26***
	(-2.57)	(-2.72)	(-2.57)	(-2.62)	(-1.58)	(-3.20)
Constant	-6.53***	-5.77***	-6.56***	-6.57***	-6.89***	-6.89***
	(-14.34)	(-12.79)	(-14.52)	(-14.57)	(-102.41)	(-29.38)
Observations	2,356,038	2,356,038	2,356,038	2,356,038	2,678,106	5,494,760
Log Likelihood	-70,623	-70,661	-70,586	-70,594	-55,469	-107,090
Pseudo R-squared	0.182	0.182	0.182	0.182	0.204	0.183

Table V
Determinants of analyst coverage timing: Cox regression

The table shows the impact of analyst familiarity on the timing of the analyst's coverage decision. The dependent variable is the time from IPO date to the first earnings forecast by the analyst within a two-year window, for sample IPOs within 1996 – 2009. Columns (1) to (4) include analysts who cover at least five sample IPOs. Column (5) reports on analysts working with the Top 20 brokers in terms of number of sample analysts. Column (6) reports on the full coverage sample. All models are estimated using Cox regression, with adjustment for right censoring at the end of the two-year window. We define the variables in Table I. We do not report coefficients for industry and IPO-year indicators for brevity. We report robust z-statistics adjusted for two-way clustering at both firm and year level in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
local	0.06**		0.03	0.10***	0.07*	0.07***
	(2.23)		(1.62)	(3.39)	(1.71)	(3.29)
distance_log		-0.01***				
		(-2.90)				
local*specialist			0.08*			
			(1.75)			
local*underwriter				-0.11***		
				(-2.67)		
specialist	0.31***	0.31***	0.30***	0.31***	0.34***	0.35***
	(10.51)	(10.51)	(13.20)	(10.53)	(14.12)	(16.43)
underwriter	0.77***	0.77***	0.77***	0.80***	0.63***	0.77***
	(15.92)	(16.04)	(15.93)	(16.24)	(9.29)	(17.16)
ventureback	0.01	0.01	0.01	0.01	0.03	0.03
	(0.18)	(0.22)	(0.18)	(0.19)	(0.76)	(0.70)
numinst	0.00	0.00	0.00	0.00	-0.00	0.01
	(0.27)	(0.28)	(0.24)	(0.25)	(-0.05)	(0.44)
insthld	-0.07	-0.07	-0.07	-0.06	-0.02	-0.02
	(-0.80)	(-0.79)	(-0.80)	(-0.78)	(-0.34)	(-0.36)
underpricing	-0.09**	-0.09**	-0.09**	-0.09**	-0.11***	-0.08**
	(-2.22)	(-2.21)	(-2.22)	(-2.22)	(-3.07)	(-2.41)
retmth6	-0.13***	-0.13***	-0.13***	-0.13***	-0.11***	-0.12***
	(-9.97)	(-9.90)	(-10.02)	(-10.08)	(-5.28)	(-12.09)
priceadj	-0.08	-0.08	-0.08	-0.08	-0.00	-0.06
	(-1.36)	(-1.33)	(-1.35)	(-1.38)	(-0.05)	(-1.11)
mktvalue	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01
	(-0.67)	(-0.70)	(-0.67)	(-0.64)	(-1.09)	(-0.33)
experience	0.15***	0.15***	0.15***	0.15***	0.19***	0.17***
	(7.33)	(7.41)	(7.31)	(7.29)	(10.67)	(11.23)
ntik	0.07	0.07	0.07	0.07	0.09	0.05
	(1.29)	(1.29)	(1.29)	(1.28)	(1.44)	(1.09)
star	0.01	0.01	0.01	0.01	-0.01	0.04
	(0.28)	(0.22)	(0.31)	(0.27)	(-0.24)	(0.81)
Observations	14,639	14,639	14,639	14,639	10,319	20,715
Log Likelihood	-124,359	-124,362	-124,357	-124,356	-84,108	-183,089

Table VI
Determinants of analyst coverage timing: Tobit regression

The table shows the impact of geographic proximity on the timing of analyst coverage decision. The dependent variable is the number of days from IPO date to the first earnings forecast by an analyst within a two-year window. Our sample IPOs fall within 1996 – 2009. The sample is the coverage sample of analyst-firm observations where the analyst has initiated coverage within two years of the IPO. Columns (1) to (4) include analysts who cover at least five sample IPOs. Column (5) reports on the sample restricted to the Top 20 brokers in terms of number of sample analysts working for the brokers. Column (6) reports on the full coverage sample. For brevity we do not report coefficients for industry and year indicators. Robust z-statistics adjusted for two-way clustering at both firm and year level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
local	-14.99***		-11.68**	-23.06***	-14.28***	-16.20***
	(-3.52)		(-2.14)	(-4.15)	(-2.71)	(-4.43)
distance_log		1.69**				
		(2.01)				
local*specialist			-8.00			
			(-0.99)			
local*underwriter				23.28***		
				(3.08)		
specialist	-67.25***	-67.37***	-65.66***	-67.05***	-73.56***	-74.07***
	(-17.18)	(-17.20)	(-15.29)	(-17.12)	(-15.78)	(-21.06)
underwriter	-150.14***	-150.26***	-150.19***	-154.84***	-131.75***	-152.65***
	(-41.23)	(-41.22)	(-41.22)	(-38.46)	(-29.68)	(-47.38)
ventureback	2.18	1.65	2.18	2.19	-5.59	-3.05
	(0.46)	(0.35)	(0.46)	(0.46)	(-1.05)	(-0.72)
numinst	-0.95	-0.95	-0.91	-0.98	-1.38	-1.33
	(-0.28)	(-0.27)	(-0.26)	(-0.28)	(-0.34)	(-0.40)
insthld	3.88	4.20	3.80	3.88	2.94	0.99
	(0.32)	(0.35)	(0.31)	(0.32)	(0.23)	(0.10)
underpricing	16.26***	16.18***	16.24***	16.26***	20.55***	16.09***
	(3.67)	(3.64)	(3.67)	(3.67)	(4.26)	(3.87)
retmth6	27.96***	27.70***	27.94***	28.12***	27.78***	27.89***
	(10.09)	(9.97)	(10.08)	(10.16)	(8.72)	(10.47)
priceadj	23.17**	22.71**	23.13**	23.32**	16.42	21.51***
	(2.44)	(2.40)	(2.44)	(2.45)	(1.59)	(2.67)
mktvalue	4.12*	4.30*	4.13*	4.11*	4.97*	2.28
	(1.70)	(1.77)	(1.71)	(1.70)	(1.90)	(1.07)
experience	-35.72***	-35.51***	-35.70***	-35.69***	-46.18***	-40.19***
	(-16.48)	(-16.41)	(-16.48)	(-16.48)	(-17.73)	(-22.58)
ntik	-12.18***	-12.32***	-12.13***	-12.17***	-12.72***	-8.11***
	(-3.36)	(-3.40)	(-3.35)	(-3.36)	(-3.06)	(-2.91)
star	0.98	1.36	0.88	0.91	3.90	-5.50
	(0.17)	(0.24)	(0.16)	(0.16)	(0.68)	(-1.09)
Constant	301.26***	283.99***	299.38***	305.45***	379.05***	334.21***
	(5.83)	(5.31)	(5.79)	(5.89)	(18.51)	(7.80)
Observations	14,639	14,639	14,639	14,639	10,319	20,715
Pseudo R-squared	0.020	0.020	0.020	0.020	0.020	0.021

Table VII
Do firm and analyst traits matter?

This table shows whether firm and analyst traits have any effect on the relationship between analysts' geographic proximity and their coverage decisions by adding a proxy for a firm trait and an interaction term between local dummy and the firm trait based on models of column (1) in Table IV, V and VI, respectively. We define the variables in Table I. For brevity we report the results only for *local*, firm trait and the interaction term between the two. The number of observations for Logit (Cox and Tobit) is 2,356,038 (14,639) except for model (1) and (5), which is 2,004,290 (12,173) and 1,561,827 (9,988), respectively. Robust z-statistics adjusted for two-way clustering at both firm and year level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

		Logit			Cox			Tobit		
	trait	local	interaction	trait	local	interaction	trait	local	interaction	trait
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	nsegmentg	0.57***	-0.06	-0.07	0.11***	-0.00	-0.03**	-21.46***	16.51	4.48
		(10.40)	(-1.53)	(-0.68)	(4.00)	(-0.06)	(-2.24)	(-3.95)	(1.63)	(0.78)
(2)	nsegment	0.51***	0.04	-0.02	0.07***	-0.08	-0.00	-18.23***	18.54	-2.98
		(7.40)	(0.95)	(-0.40)	(2.89)	(-1.29)	(-0.11)	(-3.95)	(1.61)	(-0.43)
(3)	diversification	0.50***	0.20	-0.05	0.06**	-0.04	0.05	-16.15***	26.12	-4.44
		(7.42)	(1.32)	(-0.45)	(2.08)	(-0.38)	(1.14)	(-3.65)	(1.05)	(-0.29)
(4)	big	0.61***	-0.20**	0.08*	0.10**	-0.07*	0.03	-22.42***	14.48*	-13.33**
		(8.97)	(-2.08)	(1.79)	(2.53)	(-1.88)	(0.99)	(-3.75)	(1.72)	(-2.25)
(5)	retstddum	0.45***	0.14**	-0.16***	0.09***	-0.05	0.13***	-17.68**	7.62	-20.36***
		(7.59)	(2.52)	(-3.89)	(2.75)	(-1.41)	(3.02)	(-2.34)	(0.76)	(-3.19)
(6)	insthld	0.58***	-0.26*	-0.00	0.14***	-0.30***	-0.01	-28.07***	51.02**	-5.30
		(6.98)	(-1.95)	(-0.02)	(4.43)	(-3.13)	(-0.10)	(-3.80)	(2.23)	(-0.41)
(7)	uniqueness	0.49***	0.15**	0.09	0.09***	-0.15***	-1.15***	-18.16***	16.73	85.68
		(6.47)	(2.45)	(0.17)	(5.05)	(-2.95)	(-3.67)	(-3.93)	(1.43)	(1.36)
(8)	underpricing	0.52***	-0.02	0.17***	0.06**	-0.00	-0.09**	-14.84***	-0.30	16.33***
		(8.98)	(-0.28)	(4.50)	(2.32)	(-0.04)	(-1.97)	(-2.85)	(-0.05)	(3.56)
(9)	star	0.53***	-0.16	-0.21**	0.04*	0.18**	-0.02	-13.73***	-14.20	3.41
		(7.27)	(-1.35)	(-2.46)	(1.65)	(2.19)	(-0.36)	(-3.11)	(-1.09)	(0.55)
(10)	experience	0.76***	-0.17***	-0.43***	-0.04	0.07*	0.14***	-5.39	-6.99*	-34.35***
		(7.73)	(-4.52)	(-14.84)	(-0.52)	(1.95)	(5.12)	(-0.73)	(-1.68)	(-14.54)

Table VIII
Comparison of firm characteristics based on analyst coverage in the first half year after IPO date

We classify our sample US IPO firms into four groups based on the status of analyst coverage within half a year immediately after the IPO dates: not covered by any analysts (N), covered exclusively by local analyst who domicile in the same state as that of the underlying firms (L), covered exclusively by non-local analyst (F), and covered by both local and non-local analysts (B). We then compute the mean across firms for each group. The Difference columns report the *p*-values in parentheses from *t*-tests for differences in means. All variables are defined in Table I.

variable	Non-covered (N)	Local only (L)	Non-local only (F)	Both (B)	(N)-(L)	(N)-(F)	(N)-(B)	(L)-(F)	(L)-(B)	(B)-(F)
mktvalue	370	501	639	722	(0.40)	(0.00)	(0.00)	(0.38)	(0.17)	(0.29)
priceadj	0.01	0.01	0.00	0.08	(0.98)	(0.51)	(0.00)	(0.75)	(0.00)	(0.00)
underpricing	0.06	0.27	0.23	0.39	(0.00)	(0.00)	(0.00)	(0.31)	(0.01)	(0.00)
retmth6	-0.02	-0.01	0.03	0.08	(0.67)	(0.01)	(0.00)	(0.41)	(0.05)	(0.04)
ventureback	0.06	0.32	0.41	0.53	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)
numinst	5.59	23.89	31.39	35.41	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
insthld	0.07	0.22	0.28	0.26	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.07)
No. of firms	847	171	1701	977						

Table IX
Does local analyst coverage matter?

This table shows the impact of local analyst coverage on the target IPO firms. We keep IPOs that are either covered only by local analysts or not covered by any analysts within a time interval immediately after the IPO date, and then track these firms for coverage by three groups of analysts within the next one year: all analysts, non-local analysts, and local analysts. *localonly* is a dummy that equals one if a firm is covered by only local analysts in the initial period, zero if the firm is not covered by any analysts. We use a logit model in Panel A, with the dependent variable *cover* being a dummy that equals one if a firm is covered by any analysts belonging to the analyst group in concern, and zero otherwise. In Panel B, the dependent variable *following* is the number of analysts from each analyst group that initiate coverage on the underlying firm. We assign a value of zero if there is no analyst coverage. We report robust z-statistics adjusted for clustering at IPO issue year level in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. The numbers in the first row indicate the number of days in the initial time interval immediately after the IPO date.

Panel A Coverage likelihood within one year after the initial period

	All 182	Non-local 182	Local 182	All 365	Non-local 365	Local l365
	(1)	(2)	(3)	(4)	(5)	(6)
localonly	2.04***	0.85**	2.77***	1.87***	1.31***	2.32***
	(7.27)	(2.46)	(9.29)	(6.04)	(5.16)	(5.75)
ventureback	0.77***	1.01***	0.40	0.22	0.30	0.19
	(3.19)	(5.00)	(1.23)	(0.74)	(0.98)	(0.70)
numinst	0.02*	0.02**	0.02***	0.02**	0.01	0.03***
	(1.69)	(2.23)	(2.74)	(2.45)	(1.18)	(4.63)
insthld	2.99***	2.36***	1.88***	2.04***	2.71***	0.75
	(3.68)	(4.20)	(2.98)	(3.33)	(5.29)	(1.16)
underpricing	-0.16	-0.05	-0.39	-0.51	-0.75***	-1.15***
	(-0.58)	(-0.20)	(-1.57)	(-1.55)	(-3.45)	(-3.62)
retmth6	0.80***	0.73***	0.35*	0.75***	0.64**	0.50**
	(3.54)	(3.14)	(1.80)	(4.04)	(2.35)	(2.13)
priceadj	-0.47	-0.19	0.50	0.40	0.87**	-0.09
	(-0.47)	(-0.25)	(1.14)	(0.74)	(2.07)	(-0.11)
mktvalue	-0.00	-0.00	-0.00***	-0.00***	-0.00**	-0.00
	(-1.60)	(-1.34)	(-2.72)	(-3.04)	(-2.01)	(-1.33)
Constant	-1.97***	-2.17***	-3.62***	-2.01***	-2.48***	-3.37***
	(-7.05)	(-10.37)	(-12.55)	(-6.99)	(-8.59)	(-7.09)
Observations	1,018	1,018	1,018	863	863	863
Log Likelihood	-426.4	-419.5	-245.5	-317.4	-256.2	-175.7
Pseudo R-squared	0.293	0.199	0.349	0.222	0.167	0.246

Panel B Negative binomial regression of the Number of analyst following within one year after the initial period

VARIABLES	All 182	Non-local 182	Local 182	All 365	Non-local 365	Local l365
	(1)	(2)	(3)	(4)	(5)	(6)
localonly	0.97***	0.35	2.15***	1.48***	0.99***	2.13***
	(3.97)	(1.23)	(6.31)	(6.85)	(3.93)	(5.83)
ventureback	0.58***	0.75***	0.58**	0.17	0.49*	-0.00
	(6.48)	(6.02)	(2.30)	(0.87)	(1.84)	(-0.01)
numinst	0.04***	0.04***	0.02***	0.03***	0.02**	0.04***
	(3.80)	(3.34)	(6.51)	(5.35)	(2.26)	(4.82)
insthld	1.34***	1.43***	0.57	1.91***	2.87***	0.03
	(3.14)	(3.29)	(1.22)	(4.00)	(4.72)	(0.08)
underpricing	-0.04	0.13	-0.37	-0.61***	-0.63***	-1.11***
	(-0.21)	(0.50)	(-1.28)	(-2.92)	(-3.79)	(-3.47)
retmth6	0.57***	0.61***	0.38***	0.48***	0.39	0.42***
	(5.42)	(3.47)	(2.80)	(3.27)	(1.63)	(2.65)
priceadj	-0.23	-0.12	0.09	0.23	0.65**	-0.67
	(-0.51)	(-0.28)	(0.18)	(0.62)	(2.50)	(-0.67)
mktvalue	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00*
	(-3.32)	(-2.83)	(-4.51)	(-3.89)	(-2.95)	(-1.69)
Constant	-1.43***	-1.81***	-3.24***	-1.70***	-2.24***	-3.20***
	(-5.98)	(-8.44)	(-14.61)	(-6.54)	(-9.48)	(-9.25)
Observations	1,018	1,018	1,018	863	863	863
Log Likelihood	-966	-734	-370	-549	-371	-231