Sell Side School Ties*

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ABSTRACT

We study the impact of social networks on agents' ability to gather superior information about firms. Exploiting novel data on the educational backgrounds of sell side equity analysts and senior officers of firms, we test the hypothesis that analysts' school ties to senior officers impart comparative information advantages in the production of analyst research. We find evidence that analysts outperform on their stock recommendations when they have an educational link to the company. A simple portfolio strategy of going long the buy recommendations with school ties and going short buy recommendations without ties earns returns of 6.60% per year. We test whether Regulation FD, targeted at impeding selective disclosure, constrained the use of direct access to senior management. We find a large effect: pre-Reg FD the return premium from school ties was 9.36% per year, while post-Reg FD the return premium is nearly zero and insignificant. In contrast, in an environment that did not change selective disclosure regulation (the UK), the analyst school-tie premium has remained large and significant over the entire sample period.

JEL Classification: G10, G11, G14

Key words: Social networks, connections, analysts, directors

Certain agents play key roles in revealing information into securities markets. In the equities market, security analysts are among the most important. A large part of an analyst's job is to research, produce, and disclose reports forecasting aspects of companies' future prospects, and to translate their forecasts into stock recommendations. Therefore, isolating how, or from whom, analysts obtain the information they use to produce their recommendations is critical.

In this paper we investigate ties between sell-side analysts and management of public firms, and the subsequent performance of analysts' stock recommendations. We exploit common past experiences, namely attendance at identical educational institutions, to identify firms where analysts are more likely to gain direct access to senior management. An advantageous aspect of our network ties is that they are formed far before the information likely being transferred across them, and that the underlying tie (e.g., alumni link) is not directly related to the type of information likely being transmitted years later (e.g., company related information).

Our main goal is to test the hypothesis that analysts gain comparative information advantages through their social networks; specifically, through educational ties with senior officers and board members of firms that they cover.[1] We test this hypothesis by building portfolios that replicate sell-side analysts' recommendations and by comparing how analysts perform on firms to which they have ties, relative to firms to which they do not. Our analysis focuses on the universe of sell-side analysts and publicly traded domestic firms for which we are able to collect data on the educational background of both the analyst and senior officers of the firm she covers.

To better understand our approach, consider the following example. In 1992, two sell-side analysts covered XYZ Corp.[2] One analyst, Mr. Smith, shares a connection with the firm, defined as having attended the same academic institution as a member of the board of directors or a senior officer. Among the other stocks

[1] For much of the paper we focus only on links to senior officers, although we do present results for links to either senior officers or members of the board as well.

[2] This example comes directly from our sample, however we mask the firms' and analysts' names. We also alter the calendar dates.

he covers, Mr. Smith is also linked to CFM Corp., another large cap stock in the same industry. The second analyst, Mr. Jones, shares no educational link to either firm. As of December 1992, both analysts' rating on the stock (and the IBES consensus (median) rating) was a "HOLD."[3]

On February 10th, 1993, prior to market opening, Mr. Smith deviated from the consensus and upgraded XYZ to a BUY rating. He held the BUY rating until the stock delisted in December 1993. Mr. Jones maintained (and later reiterated) a HOLD rating, reflecting the consensus recommendation. Mr. Jones eventually dropped the stock from coverage, while the consensus recommendation remained a HOLD until the delisting date.

Following Mr. Smith's upgrade of XYZ (to which he shared a school tie), two major events pushed up XYZ's stock price. Immediately after the upgrade, on February 11, 1993, XYZ reported higher fourth-quarter and full-year earnings, beating the consensus expectation. Then, in October 1993, CFM Corp. announced its intention to acquire XYZ. XYZ's stock price rose 15.7% on the news. The merger was completed in December 1993. Figure 1 illustrates this timeline of events.

Between February 10th, 1993 and December 1993, XYZ's stock price rose by 78.6%. An investor who purchased the stock after Mr. Smith's bullish call would have outperformed a characteristic-adjusted benchmark by 52.9% over an 11-month period.

More generally, XYZ and CFM are not the only securities where Mr. Smith had an educational connection to management. Between 1993 and 2006, Mr. Smith covered a variety of stocks. Looking at his recommendations over time reveals his tendency of producing superior advice on stocks where he shares a school link to the firm. Between 1993 and 2006 a calendar time portfolio replicating his BUY recommendations (with a 1 day lag) in stocks to which he shares a link outperformed a characteristic-adjusted benchmark portfolio by 1.17% per month; the corresponding abnormal returns on his non-linked calls was only 0.01%.

[3] The consensus rating refers to the average across all analysts covering the stock; we do not have educational information on the remaining analysts.

The results in this example represent a much more systematic pattern across the universe of sell-side equity analysts. Consistent with the hypothesis that educational ties facilitate the transmission of private information, we find that analysts produce significantly better recommendations on firms to which they have an educational tie, relative to firms to which they do not.

Analysts' buy recommendations on school-tied stocks outperform buy recommendations on non-tied stocks by an average of 45 to 55 basis points per month, using 12-month calendar time portfolios following the recommendations. Therefore, a calendar time portfolio strategy exploiting only this school-tie informational advantage on buys, translates into average outperformance of 5.40% to 6.60% per year. This return differential is largely unaffected after controlling for other determinants of returns such as size, book-to-market, and momentum. Importantly, our results are not simply an artifact of a selected sample of "smart" or skilled analysts: the school tie premium is large even after removing analysts from the most connected schools and the highest quality schools (e.g., Ivy League) from our sample, and even after including analyst fixed effects in our regressions.

We do not find a similar return differential on analysts' sell recommendations. Analysts' school-tied sells perform roughly the same as their non-tied sell recommendation stocks following the recommendations. One explanation consistent with this finding is that managers are willing to reveal positive (but not negative) information about their firms. Alternatively, this would be consistent with analysts obtaining both good and bad news from their school-tied firms, but perhaps as part of a tacit agreement, acting only on the positive news.

There could be a number of mechanisms that allow information to be transferred along the networks. It may be that alumni networks allow analysts cheaper access to firm-level material information, which then allows them to form superior recommendations. For example, the analyst may have access to explicitly private conference calls with firm officials, or the network may simply reduce the cost to the analyst of obtaining or analyzing information about the firm (e.g., the analyst can obtain information about upcoming earnings with fewer calls to the firm). Alternatively, the education network may simply allow analysts to better assess managerial quality. Under this mechanism, there is not a constant flow of information in the network from the firm to the analyst, but instead some inherent information within the network about managerial quality (ex. all members of the Dartmouth network know that the Dartmouth CEO of firm ABC is quite good, while the Dartmouth CEO of XYZ is not).

In order to distinguish between these two alternatives, we exploit a regulation introduced during our sample period explicitly aimed at blocking the former mechanism of selective information transfer: Regulation FD, instated by the SEC in October of 2000. The regulation quite openly gave as its aim the ending of selective disclosure by firms to a subset of market participants. For instance, in the SEC release regarding Regulation FD, the aim was given to stop the occurrence that: "a privileged few gain an informational edge -- and the ability to use that edge to profit -- from their superior access to corporate insiders, rather than from their skill, acumen, or diligence." The SEC went on to caution that it was these selective disclosure relationships that allowed agents to: "exploit `unerodable informational advantages´ derived not from hard work or insights, but from their access to corporate insiders."[4] Our educational social networks may represent exactly this type of `unerodable informational advantage´ that the SEC targeted with Regulation FD. Specifically, if the channel that allows analysts to produce superior recommendations on school-tied stocks is selective disclosure, we may expect this superior ability to be attenuated post-Regulation FD. However, if the education network simply measures analysts' increased ability to assess managerial quality for CEOs they attended school with, it is not clear this would be affected at all by Regulation FD.

We test this hypothesis by splitting our sample to observe analysts' ability on school-tied stocks pre- and post-Regulation FD. All of our evidence points to selective disclosure being the main mechanism of information transfer along the network. All of our effects are positive, large, and significant pre-Regulation FD,

[4] Selective Disclosure and Insider Trading, SEC Release Nos. 33-7881, 34-43154, IC-24599, 65 Fed. Reg. 51716 (Aug. 24, 2000).

and small and insignificant post-Regulation FD. Specifically, when we run panel regressions of returns on buy recommendations on a school tie dummy variable, a post-Reg FD dummy variable, an interaction term (linked*post-Reg FD), and a host of firm, brokerage, and analyst-level control variables, we find that the coefficient on the interaction term is strongly negative, while the combined effect (interaction term + linked) is small (9bp) and insignificant (F-statistic of 1.18), indicating that the school-tie premium is largely absent in the post-Reg FD period. Similarly, the monthly returns of a long-short calendar time portfolio on the differences between school-tied and non-school-tied stocks pre-Regulation FD ranges between 68 to 78 basis points per month, or 8.16% (t=4.35) to 9.36% (t=3.50) per year. Post-Regulation FD, this difference is only 14 to 26 basis points per month, and is statistically indistinguishable from zero.

We construct an out-of-sample test of the impact of Reg FD by replicating our results in the United Kingdom, where there was no such law enacted at this time.[5] Over the entire sample period, we again find a large school-tie return premium on buy recommendations for UK-listed stocks: a long-short portfolio that purchases linked buy recommendations and shorts non-linked buy recommendations earns 187 basis points per month (t=2.79) in raw returns, and 167 basis points per month (t=2.20) in abnormal returns. However, unlike in the US, we see no significant difference in this premium between the pre- and post-Reg FD time periods.

We also show that the number of school ties an analyst possesses with her covered stocks strongly increases the likelihood of becoming an "All-Star" analyst (a one standard deviation increase in connections increases the probability by nearly 50%, from 9.2% to 13.6%), but *only* in the pre-Reg FD period; this result further highlights the value of social networks in precisely those times when selective disclosure is least inhibited.

[5] Regulations prohibiting the selective disclosure of material information by UK-listed firms have been a part of UK law for decades since rules on insider dealing came into force in the 1980s. Conversations with practitioners in the UK indicate that although clarifications and enhancements to these norms were put into effect in 2001 (through the Financial Services and Markets Act) and 2005 (via the Market Abuse Directive), these acts were generally not viewed as structural shifts in the disclosure environment in the same way that Regulation FD in the US was designed to be.

Lastly we perform a number of robustness checks. We also find that the school-tie outperformance is present in both large and small cap stocks, and for stocks with both high and low analyst coverage. In addition, the effect is robust when splitting our school-link universe across different dimensions: Ivy League and non-Ivy League, Top 40 (as defined by US News ranking) and non-Top 40, most linked and non-most linked schools, and controlling for school-level returns at the stock level. Finally, we show that other measures of social networks (namely same school conference) also form important information networks for analysts.

The remainder of the paper is organized as follows. Section I of the paper provides a brief background and literature review, while Section II describes the data on both firms and analysts. Section III provides the main results on analyst ability and sell-side school ties. Section IV explores the mechanism for information transfer across the network, while Section V concludes.

I. The setting

The opinions of sell-side equity analysts are among the most widely solicited, anticipated, and dissected news items in the stock market each day. Further, since analyst data is available in large quantities and in relatively standardized formats, the sell-side analyst industry offers an ideal testing ground for a number of theories of economic behavior. In this paper we use this testing ground to investigate the idea that agents' educational ties facilitate the transmission of private information into security markets.

A large literature on analyst performance supports the idea that analysts bring valuable information to the market, and have incentives to do so. Numerous studies document the potential profitability of trading on analyst recommendations (see, for example, Womack (1996), Barber et al. (2001, 2003), Jegadeesh et al. (2004)) and earnings forecast revisions (see Stickel (1991) and Gleason and Lee (2003), among others).[6] Of course, sell-side analysts have an incentive to produce

[6] See also Michaely and Womack (2007), who combine information from recommendations and earnings forecasts data and show that the subset of upgraded/downgraded recommendations "supported" by an earnings forecast revision in the same direction are the most profitable

unbiased forecasts and recommendations for investors only if they are compensated for such behavior. Due to a lack of data on direct compensation, the literature generally tests this idea by linking analyst behavior to measures of implicit incentives or career concerns. Stickel (1992) finds that highly rated "All-American" analysts (who are typically better compensated than other analysts) are more accurate earnings forecasters than other analysts, suggesting that accuracy is rewarded. Similarly, Mikhail, Walther, and Willis (1999) document that poor relative performance leads to job turnover.

An important strand of the literature, however, suggests that analysts' career concerns and the conflicts of interest inherent in equity research create an agency problem, potentially at the expense of investors who trust analyst research to be unbiased. Hong, Kubik, and Solomon (2000), find that younger analysts deviate less from the consensus than their older counterparts, consistent with the predictions of reputation-based herding models.[7] Hong and Kubik (2003) report that controlling for accuracy, analysts who are optimistic relative to the consensus are more likely to experience favorable job separations. They also find that analysts are judged less on accuracy than optimism when it comes to stocks underwritten by their employers, supporting allegations that analysts suffer from a conflict of interest when covering stocks affiliated with their brokerage houses.[8] Since we can control for investment banking affiliations, we can distinguish information effects from these agency effects throughout the paper.

Our paper is unique in that we try to isolate a channel through which analysts acquire valuable information. As such, our work is related to the recent passage of Regulation FD. Effective October 23, 2000, companies must reveal any material information to all investors and analysts simultaneously in the case of intentional disclosures, or within 24 hours in the case of unintentional disclosures. According to SEC Proposed Rule S7-31-99, regulators believe that allowing

recommendations.

[7] Chevalier and Ellison (1999) and Lamont (2002) find similar results for mutual fund managers and macroeconomic forecasters, respectively. Also see Holmström (1999) and Scharfstein and Stein (1990) for related work on career concerns.

[8] Lin and McNichols (1998), Michaely and Womack (1999), and Lin, McNichols, and O'Brien (2005) also report evidence in support of this view.

selective disclosure is "not in the best interests of investors or the securities markets generally." Several recent papers examining the impact of Regulation FD on the behavior of equity analysts conclude that the law has in fact been effective in curtailing selective disclosure to analysts (see, for example, Mohanram and Sunder (2006), Agrawal, Chadha, and Chen (2006), and Gintschel and Markov (2004)). Since our tests explore a specific possible channel of selective disclosure, they are relevant to this debate.[9]

Exploring the role of social networks, connections, and influence in financial markets is a relatively new development in the finance literature.[10] Related to our work are the findings in Hong, Kubik, and Stein (2005), who document word-of-mouth effects between same-city mutual fund managers with respect to their portfolio choices, and Kuhnen (2008), who documents a link between past business connections between mutual fund directors and advisory firms and future preferential contracting decisions.[11] Also related are the findings in Massa and Simonov (2005), documenting a relation between the portfolio choices of individual investors and their past educational backgrounds.[12]

Our empirical identification is similar to Cohen, Frazzini, and Malloy (2008), who exploit educational connections between mutual fund managers and corporate board members to identify information transfer through social networks. Hwang and Kim (2008) and Butler and Gurun (2008) also use corporate board data to identify social networks, but focus on the impact of social connections on executive compensation. The use of corporate board linkages as a measure of personal networks is common in the network sociology literature (see, for example, Mizruchi (1982, 1992), Useem (1984)). Board linkages are typically isolated by

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[9] See also Malloy (2005), who shows that geographically proximate analysts produce more accurate forecasts, but do so both before *and* after the enactment of Regulation FD; as well as Groysberg, Healy, Chapman, Shanthikumar, and Gui (2007), who document a decline in the forecast accuracy advantage of sell-side analysts over buy-side analysts after the enactment of Regulation FD.

[10] See Jackson (2005) for a survey on the economics of social networks.

[11] See also Hong, Kubik, and Stein (2004) for evidence that measures of sociability are linked to increased stock market participation, and Hochberg, Ljungqvist, and Lu (2007) for evidence of a positive impact of venture capital networks on investment performance.

[12] See also Parkin (2006), who identifies school clustering of lawyers at law firms that cannot be explained by quality or location, and a link between promotion chances in law firms and the concentration of partners with similar educational backgrounds.

looking at direct board interlocks between firms (as in Hallock (1997), "back-door" links among directors across firms (as in Larcker et al. (2005) and Conyon and Muldoon (2006)), or direct and indirect links between board members and government agencies or officials (as in Faccio (2006) and Fisman et al. (2006), among others), and have shown to be important mechanisms for the sharing of information and the adoption of common practices across firms.[13] Our approach is different in that we focus on direct links between board members and equity analysts via shared educational backgrounds.

II. Data

The data in this study is collected from several sources. We search public filings and other miscellaneous information available over the World Wide Web to construct a novel database of educational backgrounds of sell-side analysts issuing recommendations on US domestic stocks.

We start by identifying all sell-side analysts on the I/B/E/S tape who provide at least one recommendation on a domestic stock between 1993 and 2006. For each analyst, I/B/E/S provides a numeric identifier, the analyst's last name, the initial of his/her first name, and a code corresponding the analyst's brokerage firm. We use the broker translation file to reconstruct the name of the brokerage house.[14] Since our data construction methodology involves name searches, we delete observations with multiple names for a given numeric identifier or multiple identifiers for a given name. Finally, we discard teams, since I/B/E/S provides only the team members' last names but not their first name. This leads to an initial list of 8,620 analysts issuing recommendations between 1993 and 2006.

We hand-collect analysts' educational backgrounds from a variety of sources. Our main data source is Zoominfo.com, a search engine that specializes in

[13] Examples of the latter include the adoption of poison pills (Davis (1991)), corporate acquisition activity (Haunschild (1993)), CEO compensation (Khurana (2002)), and the decision to make political contributions (Mizruchi (1992)).

[14] See Malloy, Marston, and Ljunqvist (2008) for issues and problems with the I/B/E/S historical recommendation data. Note that since we use a very recent snapshot of the data (circa late 2007), after cleanups to the historical data had already been put into effect, it is likely that future snapshots of the data will produce similar results over our sample period.

collecting and indexing biographical and employment data from publicly available documents over the Web. From this site, we obtain each analyst's full name, job title, present and past employment history and the stocks covered in order to correctly identify an analyst in our initial set. We supplement the initial search with the BrokerCheck search engine available on the Financial Industry Regulatory Authority website, which contains background information on current and former FINRA-registered security investment professionals. Finally, if we are unable to determine the analyst's educational background using our primary sources, we use other available sources over the Web on a case-by-case basis to collect additional information. In building our final sample we use a conservative approach and discard observations where we are unable to uniquely associate an analyst with a specific educational background. This occurs either due to disagreement between multiple sources, or because we are unable to correctly identify the analyst.[15] For each analyst we collect the name of the academic institution attended for either an undergraduate or a graduate degree.[16]

Biographical information for senior company officers and board members is provided by Boardex of Management Diagnostics Limited. The data contain relational links among board of directors and other corporate officials. Links in the dataset are constructed by cross-referencing employment history, educational background and professional qualifications. For each firm, we use the link file to reconstruct the annual time series of identities and educational background of senior officers (defined as CEO, CFO or Chairman) and board members. The final data contain current and past roles of company officials with start-year and end-year, a board dummy and the academic institution for undergraduate and graduate

[15] For example, if according to I/B/E/S a person named A. Summer covers technology stocks for Goldman Sachs in 1999, but our web searches uncover an Alan Summer and an Amy Summer, both of whom were analysts for Goldman Sachs covering technology stocks in 1999, we would not be able to uniquely match this analyst.

[16] One drawback of our dataset is that graduation years are missing for 70% of the final sample since most of the data is extracted from company releases or other public filings, which tend to omit graduation years. Information on degree type is also missing for about 35% of analysts. We have tried to collect these additional data items from each academic institution's alumni network but have been unable to collect a large enough sample to date, since many universities restrict access to their alumni network and/or require written consent of the alumnus before releasing this information.

degree (where available). We hand match institutions from our analyst data and Boardex and create a unique numeric identifier.[17]

We hand collect data on a number of educational institution characteristics. We collect the rankings from US News and World Report between 1995-2006 and match it back to our sample. US News and World annually ranks the Top 100 universities in the United States. We also collect data on the location of and conference of all universities in our sample from the universities' websites.

Finally, we match the firms associated with all company officials and sell-side analysts to accounting and stock return data from CRSP/COMPUSTAT. Our final sample includes educational background data on 1,820 analysts issuing a total of 56,994 recommendations over 5,132 CRSP stocks between October 30th, 1993 and December 20th, 2006.

Table I reports summary statistics for the matched samples of firms-boards-analysts. From Panel A, we average 604 analysts and 5,746 recommendations per year, which comprise 23% of the universe of sell-side analysts and 23% of the total number of recommendations per year.[18] Our sample of firms averages 1,705 per year, which comprise 74% of total market value of CRSP stocks covered by sell-side analysts.

In Panel B we report summary statistics by firm-year. The mean coverage per firm is around 5 analysts. The average size percentile is 0.78 while the average book-to-market percentile in 0.37, reflecting the known fact that analyst coverage tends to be skewed towards larger cap growth stocks.

Table II reports summary statistics on our sample of school ties, broken down by academic institution. Panel A reports the average number of analyst ties to senior corporate officials, while Panel B reports the average number of analyst ties to firm boards of directors. Harvard University accounts for 18.53% of analyst ties to senior officials in our sample, and 18.2% of analyst ties to corporate boards;

[17] See also Cohen, Frazzini, and Malloy (2008) for additional details on data construction and matching using the BoardEx data.
[18] Note that in unreported tests we have verified that the characteristics of our sample are very similar to those of the entire database of I/B/E/S recommendations over this time period (e.g., in terms of the proportion of buys/sells; average calendar-time portfolio returns of all buy recommendations, etc.).

Ivy League schools in general account for 43.7% of analyst ties to senior officials, and 48.5% of analyst ties to corporate boards.[19]

Additional summary statistics on the percentage of linked stocks, the number of linked stocks, and the number of stocks covered for different categories of analysts is reported in Table A1 in the Internet Appendix.[20]

III. Results: Returns to sell-side recommendations

In this section we examine the stock return performance of recommendations by sell-side analysts on securities to which they have school ties. We test the hypothesis that recommendations issued on stocks with school ties outperform recommendations issued on stocks without ties.

To assess the relative performance of sell-side recommendations we use a standard calendar time portfolio approach.[21] We classify a firm as having educational ties to an analyst if that analyst attended the same academic institution as a senior officer (or, in alternate specifications, if he/she attended the same school as a senior officer *or* a member of the board). We use the I/B/E/S numeric recommendation code to assign each recommendation to one of two portfolios: (1) a BUY portfolio consisting of all stocks upgraded relative to the previous recommendation, or initiated, resumed or reiterated coverage with a buy or strong buy rating, and (2) a SELL portfolio, consisting of all stocks downgraded relative to the previous recommendation, initiated, resumed or reiterated coverage with a hold, sell or strong sell rating, or dropped from coverage by the analyst. We also consider a version of both portfolios using only upgrades or downgrades. If the brokerage house does not report a stock as dropped from coverage and a recommendation is not revised or reiterated within twelve months, we let it expire.

Our portfolios are constructed as follows. For the BUY portfolio, we begin by identifying each BUY recommendation as described above. For each buy recommendation, we skip a trading day between the recommendation date t and

[19] Note that our results are not driven by a few particular schools (e.g., Ivy League), as we show later in the paper.

[20] The Internet Appendix can be found at http://www.afajof.org/supplements.asp.

[21] See also Barber, Lehavy, and Trueman (2005), and Barber, Lehavy, McNichols, and Trueman (2005).

investment, and purchase the recommended stock at the close of day *t+1.* By waiting a trading day we exclude the recommendation-date returns and ensure that the portfolios are based on available information. Each recommended stock remains in the portfolio until it is either downgraded, dropped from coverage, or the underlying recommendation expires. Again, we skip a day between an event that causes a stock to be unloaded and the actual disinvestment: e.g. if a stock is downgraded at date *t,* we unwind the position at the close of date *t+1.* If more than one analyst recommends a particular stock on a given date, then the stock will appear multiple times in the portfolio, once for each recommendation.

Finally, we compute value weighted calendar time portfolios by averaging across analysts, weighting individual recommendations by the analyst's recommendation code. For the BUY portfolio, we reverse-score the recommendation codes so that a Strong Buy is set equal to 5 (instead of 1, as it is in the raw data) and a Strong Sell is set equal to 1, so that a higher weight indicates a relatively more bullish recommendation. We use the same method for the SELL portfolio, with the exception that in the final step we use the actual recommendation codes as portfolio weights; i.e., a Strong Buy is set equal to 1 and a Strong Sell is set equal to 5, so that a higher weight indicates a relatively more bearish recommendation.

This approach yields a time series of returns for each portfolio and has the advantage of corresponding to a simple investment strategy of following sell-side recommendations, mimicking both the directional advice and the holding period implied by the timing of the revisions.

For each stock, we compute risk-adjusted ("DGTW") returns as in Daniel et al. (1997) by subtracting the return on a value weighted portfolio of all CRSP firms in the same size, (industry-adjusted) market-to-book ratio, and one year momentum quintile, from the stock's raw return. We update the 125 characteristic portfolios at the end of June of each year using conditional sorts, and adjust the market-to-book ratios using the 48-industry classifications from Ken French's website.[22]

[22] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table III presents calendar time portfolio returns for our sample of BUY recommendations, and illustrates one of our main results. BUY recommendations with school ties earn 1.59% per month in raw returns, while BUY recommendations without school ties earn 1.04%. A long/short portfolio which purchases stocks after BUY recommendations by school-tied analysts and shorts stocks after BUY recommendations by non-school-tied analysts earns 55 basis points per month (t=3.75), which translates into an annual premium of 6.60%. This long/short portfolio has the advantage that it conditions on the signal of the recommendation (BUY in both cases), and so isolates solely the school-tie premium portion of the analysts' recommendations. If we extend the sample to examine ties between analysts to either senior management or the board of directors, the return on this long-short portfolio is slightly smaller at 45 basis points per month, or 5.40% percent per year (t=3.87). The risk-adjusted abnormal returns are given in the third and fourth columns of Table IV. The buy recommendations on stocks without school ties earn basically a zero abnormal return. In contrast, the buy recommendations on stocks where the analyst has school ties precede large abnormal returns; thus the school-tie premium is largely unaffected by other return determinants (47 basis points, (t=3.96)). In later tests we also show that this school tie premium is not driven by analysts from the most connected schools or from a certain group of schools (e.g., Ivy League).

The last two columns of Panel A report portfolio returns for the subset of upgrades only (i.e., upgrades to buy or strong buy only, excluding initiations and reiterations). The long-short portfolio of tied minus untied upgrades again earns large returns, ranging from 29 to 35 basis points per month over the full sample period.

Panel B of Table III presents results for the sample of SELL recommendations. Column 2 of Panel B indicates that we are unable to reject the hypothesis of no difference between the raw returns of sell recommendations by analysts with school ties and those without. The next two columns extend these findings to DGTW-adjusted returns. For the sample of analysts with links to either senior management or the board of directors, the returns on sell recommendations by analysts with school ties are actually significantly higher than those by analysts without ties. However, when we explore this result more carefully in a regression context below in order to control for other determinants of returns, we find that there is no difference between the abnormal returns following linked and non-linked sell recommendations.

Overall, our calendar time portfolio tests on the buy recommendations of linked analysts reveal an economically and statistically significant channel through which analysts produced superior recommendations. Our results on sell recommendations suggest that either this information advantage does not extend to negative information, or that incentives not to reveal such negative information are strong.

To ensure that our results are not driven by something specific about linked analysts or firms, we also employ panel regressions of the returns to buy/sell recommendations on two school tie dummy variables (one indicating a link to senior management, and the other indicating a link to senior management or a member of the board), and a host of firm, broker, and analyst-level control variables. The dependent variable is daily returns (Ret), and control variables include: a dummy equal to one if the analyst attended a school in the Top 10 in terms of number of links to firms; a dummy equal to one if the analyst attended an Ivy League university; a dummy equal to one if the analyst attended a university ranked in the Top 40 by US News and World Report; lagged marked capitalization of the stock (Size); book-to-market (BM); past one-year momentum (Past Returns); a measure of analyst experience, equal to the number of years an analyst has been making recommendations on I/B/E/S; an affiliation dummy, equal to one if the analyst is employed by a bank that has an under-writing relationship with the covered firm[23]; an All-Star dummy variable, equal to one if the analyst is listed as an "All-Star" in the October issue of Institutional Investor magazine in that year[24]; a measure of brokerage size, equal to the total number of analysts that work for a given analyst's brokerage house; and fixed effects for recommendation month,

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[23] The list of affiliated analysts is from Ljungqvist at al. (2006).
[24] The list of "all-star" analysts is from Ljungqvist at al. (2007).

industry, and analyst where indicated. Regressions are run daily, but the coefficients reported in Table IV are converted to represent monthly returns (in percent); all standard errors are adjusted for clustering at the recommendation month level.

Table IV reports the regression results for BUY recommendations. Columns 1-2 show that the coefficients on the school tie dummies are positive, significant, and of the same order of magnitude as the return results from the portfolios (between 37-48 basis points per month), again indicating that buy recommendations by analysts with school ties earn significantly higher returns than those by analysts without such ties. Columns 3-5 report similar results even after controlling for whether or not the analyst attended a highly connected school (Top 10 Most Linked), or two measures of high "quality" schools (Ivy League and Top 40 US News). Columns 3-5 also show that the school tie premium is nearly unchanged after including industry fixed effects, and firm- and analyst-level controls. Columns 6 and 7 then show that the school tie premium remains large and significant even when including the stricter analyst fixed effects. Since including analyst fixed effects explicitly isolates variation within an analyst's portfolio (i.e., performance on tied versus non-tied stocks for the *same* analyst), this result indicates that our main school tie affect is unlikely to be an artifact of a selected sample of "smart" of skilled analysts.[25]

Table V presents the analogous regression results for the sample of SELL recommendations. In every column, the impact of school ties is small and insignificant. In the strictest specification in column 7, which includes analyst and month fixed effects and the full set of controls, the coefficient on the school tie dummy is negative, but small and insignificant. In the analogous specification for downgrades (unreported), we also find a negative coefficient on the school tie dummy, but again this coefficient is modest (-0.16) and insignificant (t=1.05).[26]

[25] We ve also clustered by analyst in all regressions, and the standard errors (and resulting *t*-stats) are nearly identical. We report these in the Internet Appendix in Table A8.

[26] In addition to these tests, and in order to rule out a potential sample selection bias caused through the measurement of our connectedness measure (e.g., the sample for whom we can identify any links being correlated with firm performance and survival), we run all tests on only the sample for which we are able to definitively identify *all* potential links from the analyst to senior managers

IV. Mechanism

Our results on the outperformance of buy recommendations by analysts with school ties suggest a statistically and economically important channel for the transfer of private information. In this section we explore possible hypotheses regarding the manner in which this information might be conveyed, the impact of school ties on analyst status, and the types of information being transferred across these networks.

A. Regulation on Selective Disclosure to Analysts

As noted above, our main test to distinguish between direct information transfer as the driver of our findings versus superior assessments of managerial quality is to split the sample pre- and post-Reg FD. The pre-Reg FD period was allegedly a time period plagued with problems of selective disclosure between firms and equity analysts, and the law put in place was expressly designed to curb these practices. The motivation expressed by the SEC in their release[27] on Regulation FD suggests that the school ties we identify in our tests are exactly the sort of private information channel between firms and analysts that the regulation was designed to address. The fact that our results are significantly weaker in the post-Reg FD period suggests that the regulation was effective in curbing the apparent information advantage that analysts gain through their school networks.

To test this idea formally, we employ panel regressions on buy recommendations as in Table IV, except that we now also include a Post-Reg FD dummy variable, and an interaction term (Link Mgmt*Post-Reg FD), in addition to the school tie dummy variable and control variables mentioned earlier. Column

(i.e., where we have school information for the analyst, and all three senior managers). In this subsample, we find that results on buys are nearly identical, while the results on sells are statistically insignificant, but actually become more negative, so more supportive of school ties having some impact also on sell recommendations. In fact, in the analog of Column 1 of Table V for returns following downgrades on this subsample, linked downgrades significantly underperform non-linked downgrades (-25 bp per month, (t=2.15)). We thank an anonymous Associate Editor for suggesting these tests. These results are reported in Table A9 in the Internet Appendix.

[27] Selective Disclosure and Insider Trading, SEC Release Nos. 33-7881, 34-43154, IC-24599, 65 Fed. Reg. 51716 (Aug. 24, 2000).

2 of Table VI presents the key test of the impact of Reg FD on the school-tie return premium. The coefficient on Link Mgmt measures the impact of school ties pre-Reg FD, and its magnitude of 0.72 (t=3.61) implies an annual return premium of 8.64% per year. The interaction term (Link Mgmt*Post-Reg FD) is designed to capture the effect of school ties in the post-Reg FD time period.[28] We find that the coefficient on the interaction term is strongly negative and significant, while the combined effect (i.e., [Link Mgmt*Post-Reg]+[Linked to Mgmt]) is small (9bp=-63bp+72bp) and insignificant (F-statistic of 0.46, p>0.50), indicating that the school-tie premium is largely absent in the post-Reg FD period. Column 3 reports results from the same test, but only for the subset of analysts that are in the sample both pre- *and* post-Reg FD. This is to control for a possibility that connected analysts may for some reason leave the sample post-Reg FD. From Column 3, the results are virtually identical on this sample of analysts.[29]

We also report calendar time portfolio results for the pre- and post-Reg FD time periods in Panel A of Table VII. Panel A indicates that the large returns to school ties for buy recommendations are concentrated in the pre-Reg FD period. Specifically, the school tie premium in the pre-Reg FD period ranges between 68 to 78 basis points per month, or 8.16% (t=4.35) to 9.36% (t=3.50) per year.[30] Post-Regulation FD, this difference is only 14 to 26 basis points per month, and is statistically indistinguishable from zero. Panel A also reports results for sell recommendations, splitting the sample in the same way; not surprisingly given our earlier results on sells, we find no significant differences between the two periods for sell recommendations.

We also construct an out-of-sample test of the impact of Reg FD by replicating our results in the United Kingdom, where there was no such regulation enacted at this time. Again we form buy-sell portfolios of linked and non-linked

[28] We exclude month fixed effects in these regressions because the model cannot be estimated with a post-Reg FD dummy and month fixed effects jointly (as they are collinear).
[29] We have also run these regressions using a firm fixed effect, and a firm-by-time period (pre- vs. post-Reg FD) fixed effect. After doing so, the school tie premium remains virtually unchanged, suggesting that this result is not driven by any special characteristics of linked vs. non-linked stocks, nor by a characteristic of these linked stocks that changed in the pre- and post-Reg FD time periods.
[30] See the Appendix, Table A2, for additional specifications using abnormal returns, upgrades, etc. These results are very similar to those reported here.

recommendations, but we now restrict our analysis to UK-listed stocks for which we have analyst recommendations on I/B/E/S and available educational background information on both the analyst and the senior officers of the firm.[31] Panel B of Table VII shows that over the entire sample period, we again find a large school-tie return premium on buy recommendations for UK-listed stocks: a long-short portfolio that purchases linked buy recommendations and shorts non-linked buy recommendations earns 187 basis points per month (t=2.79) in raw returns, and 167 basis points per month (t=2.20) in abnormal returns. Again we find no significant school-tie premium on sell recommendations. However, unlike in the US, we see no significant difference in the school-tie premium on buy recommendations between the pre- and post-Reg FD time periods.[32] The point estimates of the school-tie premium are actually slightly higher (although not significantly) in the post Reg FD time period. This gives confirming evidence that the Reg FD effect we find in the main (US) sample is in fact driven completely by this new regulation against selective disclosure. In the absence of regulatory change, school ties continue to confer significant benefits to analysts.

In summary, all of our findings indicate that Regulation FD had a large impact on the school-tie premium that we identify in this paper, suggesting that the most likely mechanism driving the superior performance of analysts on their school-tied recommendations is direct information transfer.[33]

Our results on the impact of Regulation FD are also consistent with several recent papers that examine the impact of the law on the behavior of equity

[31] Analogous to our US sample, we collect educational data on I/B/E/S analysts issuing recommendations on stocks traded in the UK, as defined by the I/B/E/S country exchange code. We hand matched firms from the Boardex sample to I/B/E/S using company names. Daily returns (in local currency) are from Factset. Market equity and book equity are from Compustat Global. Note that the coverage of our sample is sparse for non-US data: By requiring educational information on I/B/E/S analysts covering UK stocks, we limit our sample to an average of 26 analysts, 69 stocks, and 131 recommendations per year over the 1993-2006 time period.

[32] For brevity we only report results for links to senior management, and for raw returns (in Panel C). Results are very similar for the full set of specifications used earlier.

[33] Note that Cohen, Frazzini, and Malloy (2008) do not find a large impact of Reg FD on the return premium that mutual fund managers earn on their school-connected stocks relative to their non-connected stocks. This could be due to a different mechanism at work in the case of mutual fund managers. It could also be due to the fact that equity analysts were under intense scrutiny during this time period, not only as a result of Reg FD, but also due to alleged conflicts of interest that led to several new policy measures being enacted by the SEC, NASD, and NYSE, and which culminated in the Global Settlement of 2003.

analysts and conclude that the law has in fact been effective in curtailing selective disclosure to analysts (see, for example, Mohanram and Sunder (2006), Agrawal, Chadha, and Chen (2006), and Gintschel and Markov (2004)). For example, Mohanram and Sunder (2004) find that analysts who may have had preferential links with firms they covered, such as analysts from large brokerage houses, tended to have greater forecast accuracy pre-Reg FD, but were unable to maintain their forecasting superiority post-Reg FD. Coupled with our findings, these results suggest that Regulation FD has been successful in leveling the information playing field for sell-side research, and likely signals a shift towards greater independence from senior management on the part of financial analysts.

B. Strength of School Ties, All-Star Value, and Robustness Checks

In this section we explore some additional implications of our results. First, if school ties are driving the results we find, then stronger ties should result in an increased strength of school tie premium for these analysts. Columns 4 and 5 in Table VI test this using a variable (Frac Link to Analyst) equal to the percentage of top firm management (board members + senior management) to whom the analyst has a link. From Table VI, this proxy for the strength of the school tie link is positively and significantly related to the school tie premium. This holds even after controlling for the effect of having school ties in general (Column 5). The coefficient in Column 5 implies that a one standard deviation increase in the strength of school ties to management increases the school tie premium by nearly 1% per year.

In addition to this link-strength measure, we also create a new measure of social ties. If social networks are an important source of information advantage for analysts, then other types of social networks may provide the same advantage. We attempt to show one alternative measure in Table VI. The measure we use is common athletic conference (for example, Big 10). Attending the same athletic conference could be an impetus for information sharing (or could reduce the cost of information gathering) in much the same way as school alumni relationships. We thus create a new categorical variable *Linked by Conf*, equal to one if the analyst attended a school that competes in the same athletic conference as a senior manager's, and zero otherwise. From Columns 6 and 7, in addition to having an alumni connection, attending schools in the same athletic conference does afford the analyst a significant advantage in collecting information on the firm.[34] Specifically, from Column 7, including all controls, the analyst's recommendations on these conference-linked stocks outperform by 15 bp per month (t=1.98), nearly half the magnitude of the alumni result, but still significant.[35]

Another way to quantify the value of the social networks we isolate in this paper is to test the extent to which school ties predict the probability of that analyst becoming an All-Star. We run OLS and probit regressions forecasting All-Star status and find that the number of school ties is a strong positive predictor of the likelihood of being an All-Star. A one standard deviation increase in number of connections increases the probability of being an All-Star by nearly 50% (from 9.2% to 13.6%). These results are reported in Table A4 in the Internet Appendix.

In order to better understand the type of information being transferred across the networks, we also examine the relative forecast accuracy of analysts with school ties, under the hypothesis that the information advantage gained by linked analysts is specifically related to information that would allow an analyst to better predict earnings per share numbers reported by firms. We find no significant differences in relative forecast accuracy (or relative forecast optimism) between the forecasts of analysts with school ties and those without.[36] These results suggest that the school-tie return premium we document in Section III is unlikely to relate to information obtained about future earnings per share numbers. In unreported tests we also look at the propensity of buys among school tied and non tied firms

[34] Note that in both specifications we include *Linked to Mgmt*, to orthogonalize against those instances where the analyst and senior manager attended the same school.
[35] We also find similar effects using common state of school attended (e.g., Iowa and Iowa State), although a bit weaker.
[36] Following Malloy (2005) and Clement (1999) and using 1- and 2-year ahead earnings forecasts drawn from the I/B/E/S Detail File, we run Fama-MacBeth cross-sectional regressions of de-meaned absolute forecast error (*DAFE)*, proportional mean absolute forecast error (*PMAFE*), and relative optimism (*OPT*) on a variety of analyst characteristics plus a dummy variable equal to one if the analyst is linked to the board of directors or a senior officer of the firm being covered. Although the sign on the dummy variables in the *DAFE* and *PMAFE* regressions is consistently negative (indicating that linked analysts are more accurate), the coefficients are generally insignificant. These results are available on request.

that later announce a merger, as well as merger-related-news return decompositions, and find little difference, suggesting that the passing of merger-related information is unlikely to fully explain our findings.

We also run a number of robustness checks on our results. These include splitting our sample by a series of stock-, analyst- and school-characteristics. We report these results in Tables A5 and A6 in the Internet Appendix.

V. Conclusion

In this paper we investigate information dissemination in security markets. We use the recommendations of sell-side equity analysts as a laboratory to study the impact of social networks on agents' ability to gather superior information about firms. In particular, we test the hypothesis that analysts' school ties to senior corporate officers impart comparative information advantages in the production of analyst research. Our main result is that equity analysts outperform on their stock recommendations when they have an educational link to that company. A simple portfolio strategy of going long the buy recommendations of analysts with school ties and going short the buy recommendations of analysts without ties earns returns of 6.60% per year in the full sample.

This result suggests that analysts' social networks facilitate the direct transfer of information, or alternatively that these networks simply allow analysts to better assess managerial quality. In order to distinguish between these two hypotheses, we exploit a regulation introduced during our sample period explicitly aimed at blocking the former mechanism of selective information transfer: Regulation FD, instated by the SEC in October of 2000. We find a large effect of the law: pre-Reg FD the return premium from school ties is 9.36% per year, while post-Reg FD the return premium is nearly zero and insignificant. A similar test in the UK, which did *not* experience a change in the disclosure environment at this time, reveals a large and significant school-tie premium for buy recommendations over the entire sample period, both pre- and post-2000.

Taken together, our findings suggest that agents in financial markets can gain informational advantages through their social networks. In addition, laws designed to block these types of information pathways can be effective in curbing selective disclosure. The magnitude of our results indicates that informal information networks are an important, yet under-emphasized channel through which private information gets revealed into prices. Identifying the types of information transferred across social networks and the extent to which social networks are important in other information environments can provide us with a richer understanding of information flow, and price evolution, in security markets.

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Table I: Summary statistics

This table reports summary statistics for the sample of sell side analysts and their covered stocks between 1993 and 2006. The sample of analysts includes all sell side analysts from the merged CRSP/IBES/BOARDEX issuing recommendations on US stocks between 1993 and 2006. The sample of stocks includes the stocks from the merged CRSP/IBES/BOARDEX data with non missing information on the educational background of members of the board of directors and senior officers of the firm (CEO, CFO or Chairman). Panel A reports the data coverage as a fraction of the total number of IBES analysts, the total number of stocks, the total market value of covered stocks (ME), and the total number of IBES recommendations (Recs). Panel B reports pooled means. Analyst coverage is the # of analysts providing recommendations for a given stock in the prior 12 months.

Panel A: coverage of IBES/CRSP universe

Year	# analysts	#stocks	# recs	fraction of analysts	fraction of stocks	fraction of ME	fraction of recs
1993	153	650	1,066	0.14	0.22	0.52	0.10
1994	243	883	2,468	0.15	0.25	0.54	0.12
1995	283	1,022	2,701	0.16	0.28	0.56	0.12
1996	349	1,166	2,785	0.17	0.28	0.55	0.13
1997	402	1,396	3,339	0.17	0.33	0.66	0.15
1998	516	1,574	4,104	0.19	0.37	0.72	0.16
1999	602	1,737	4,897	0.21	0.44	0.75	0.19
2000	645	1,915	5,562	0.23	0.52	0.84	0.24
2001	682	1,905	6,397	0.25	0.61	0.86	0.28
2002	756	2,203	10,218	0.27	0.68	0.90	0.30
2003	813	2,167	8,829	0.30	0.71	0.90	0.33
2004	958	2,340	9,081	0.33	0.73	0.86	0.36
2005	1,078	2,474	9,374	0.36	0.76	0.88	0.40
2006	971	2,441	9,623	0.33	0.74	0.88	0.38
Average	604	1,705	5,746	0.23	0.49	0.74	0.23

Panel B: pooled observations	mean	median	min	max	std
Analyst coverage per firm	4.97	4.00	1.00	32.00	3.84
Size percentile	0.78	0.84	0.01	1.00	0.20
Book-to-market percentile	0.37	0.33	0.01	1.00	0.25
12-month return percentile	0.52	0.53	0.01	1.00	0.29
# of schools per year	766	766	707	796	28
# of board members per year	8,388	8,160	2,355	14,389	4,176
# of senior officers per year	3,769	3,963	1,183	5,832	1,624

Table II: Links Between Sell Side Analysts and Firm's Management by Academic Institution

This table shows summary statistics of the ties among sell side analysts and US traded firms based on educational backgrounds between 1993 and 2006. The sample of analysts includes all sell side analysts from the merged CRSP/IBES/BOARDEX issuing recommendations on US stocks between 1993 and 2006. The sample of stocks includes the stocks from the merged CRSP/IBES/BOARDEX data with non missing information on the educational background of members of the board of directors and senior officers of the firm (CEO, CFO or Chairman). In Panel A we classify a stock as having an educational tie to the analyst if he/she attended the same institution as a senior officer (defined as either the CEO, CFO or Chairman of board). In panel B we classify a stock as having educational ties to the analyst if he/she attended the same institution as a member of the board of directors. The table reports the distribution of the total number of educational links between 1993 and 2006 by academic institution.

Panel A: Analyst tied to firm's senior officers				Panel B: Analyst tied to board of directors			
Rank	Academic institution	# of ties	% of total	Rank	Academic institution	# of ties	% of total
1	Harvard University	941	18.53	1	Harvard University	2,300	18.22
2	University of Pennsylvania	522	10.28	2	Columbia University	1,139	9.02
3	New York University	350	6.89	3	University of Pennsylvania	1,065	8.44
4	Stanford University	311	6.12	4	New York University	1,006	7.97
5	Columbia University	288	5.67	5	Yale University	717	5.68
6	Cornell University	173	3.41	6	Stanford University	597	4.73
7	M.I.T.	168	3.31	7	M.I.T.	491	3.89
8	Yale University	155	3.05	8	Cornell University	437	3.46
9	University of Chicago	140	2.76	9	UC Berkeley	347	2.75
10	UT Austin	137	2.7	10	University of Chicago	317	2.51
Others		1,893	37.28	Others		4,205	33.32
Ivy League		2,220	43.72	Ivy League		6,122	48.51
All		5,078	100	All		12,621	100

Table III: Returns to School Ties, 1993–2006

This table shows calendar time portfolio returns. We classify a stock as having an educational tie to the analyst if he/she attended the same institution as a senior officer (CEO, CFO or Chairman) or a board member. Each recommendation is assigned to one of two portfolios: (1) a BUY portfolio consisting of all stocks upgraded with respect to the previous recommendation, or initiated, resumed or reiterated coverage with a buy (IBES code = 2) or strong buy (IBES code = 1) rating, and (2) a SELL portfolio, consisting of all stocks downgraded with respect to the previous recommendation, initiated, resumed or reiterated coverage with a hold (IBES code =3), sell (IBES code = 4) or strong sell (IBES code = 5) rating or dropped from coverage. If the brokerage house does not report the stock as dropped from coverage and a recommendation is not revised or reiterated within twelve months, it is considered expired. We skip a trading day between recommendation and investment (disinvestment). For the BUY portfolio each recommended stock is held until it is either downgraded, dropped from coverage, or the recommendation expires. We compute value weighted portfolios by averaging across analysts, weighting individual recommendations by the IBES recommendation code; for the BUY portfolio, we reverse these recommendation codes so that a strong buy is set to 5 and a strong sell is set to 1. The SELL portfolio is constructed in a similar fashion with the exception that that the original IBES recommendation codes (i.e., strong sell=5, and strong buy=1) are used as portfolio weight. We report average returns and DGTW-adjusted returns for the period 1993 to 2006. DGTW characteristic-adjusted returns are defined as raw returns minus the returns on a value weighted portfolio of all CRSP firms in the same size, (industry-adjusted) market-book, and 1-year momentum quintile. Returns are in monthly percent. L/S is the average return of a zero cost portfolio that holds the portfolio of linked stocks and sells short the portfolio of non-linked stocks. t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: Buy recommendations	Buy recommendations (level)				Only upgrades			
	Raw returns		Abnormal returns		Raw returns		Abnormal returns	
No shared educational background	**1.04**		0.04		**1.35**		**0.31**	
	(1.97)		(0.43)		(2.81)		(3.14)	
Linked recommendations		L/S		L/S		L/S		L/S
Analyst linked to senior management	**1.59**	**0.55**	**0.51**	**0.47**	**1.65**	0.29	**0.61**	0.30
	(3.04)	(3.75)	(3.19)	(3.96)	(3.16)	(1.71)	(2.86)	(1.93)
Analyst linked to senior management or board of directors	**1.49**	**0.45**	**0.44**	**0.40**	**1.70**	**0.35**	**0.62**	**0.31**
	(2.91)	(3.87)	(3.24)	(4.63)	(3.35)	(2.32)	(3.49)	(2.30)

Table III: Returns to School Ties, 1993–2006 (continued)

Panel B: Sell recommendations	Sell recommendations (level)				Only downgrades			
	Raw returns		Abnormal returns		Raw returns		Abnormal returns	
No shared educational background	1.03 (1.83)		-0.17 -(1.31)		1.06 (1.81)		-0.21 -(1.45)	
Linked recommendations		L/S		L/S		L/S		L/S
Analyst linked to senior management	**1.10** (2.05)	0.07 (0.46)	0.10 (0.61)	0.27 (1.92)	**1.26** (2.20)	0.20 (0.85)	0.25 (1.01)	0.46 (1.94)
Analyst linked to senior management or board of directors	**1.08** (2.08)	0.05 (0.49)	0.05 (0.37)	**0.22** (2.26)	**1.09** (2.05)	0.03 (0.22)	0.05 (0.34)	0.26 (1.82)

Table IV: School Tie Regressions for Buy Recommendations

This table reports panel regressions of returns on buy recommendations of analysts. The dependent variable is future returns (Ret). The regressions were run daily, but coefficients have been adjusted to represent monthly returns in percent. The first 2 variables are categorical variables of whether or not the analyst is linked in an education network to the given firm on which she is making a recommendation: (i) *Linked to Mgmt* indicates the analyst is linked to the senior officers, (ii) *Linked to Either* indicates the analyst is linked to either the senior officers or the board of directors. *Top 10 Most Linked* is a categorical variable indicating if an analyst attended a school with the highest number of links to senior management (or the board of directors) in our sample. *Ivy League* is a categorical variable indicating if an analyst attended a school in the Ivy League. *Top 40 US News* is a categorical variable indicating if an analyst attended a school ranked in the Top 40 National Universities in US News and World Report. *Size* is the market capitalization of the firm, *BM* is the book-to-market ratio of the firm, and *Past Returns* is the past one-year stock return of the firm. *Analyst Experience* is equal to the number of years the analyst has been making recommendations recorded in I/B/E/S. *Affiliation* is a categorical variable that measures whether or not the given firm has an underwriting relationship with the analyst's brokerage. *All Star* is a categorical variable equal to 1 if the investor was voted an all star analyst in the October issue of Institutional Investor magazine for the given year. *Brokerage Size* is the total number of analysts that work at the given analyst's brokerage house. Fixed effects for month (Month), analyst (Analyst), and industry (Indus) using the Fama-French industry definitions, are included where indicated. All standard errors are adjusted for clustering at the month level, and t-stats using these clustered standard errors are included in parentheses below the coefficient estimates. 5% statistical significance is indicated in bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret	**Ret**	**Ret**	**Ret**	**Ret**	**Ret**	**Ret**
Linked to Mgmt	**0.48**		**0.43**	**0.44**	**0.43**	**0.39**	**0.32**
	(4.23)		(3.66)	(3.77)	(3.61)	(3.30)	(2.51)
Linked to Either		**0.37**					
		(5.16)					
Top 10 Most Linked			0.04				
			(0.67)				
Ivy League				0.01			
				(0.18)			
Top 40 US News					0.05		
					(0.69)		
Size			**-0.01**	**-0.01**	**-0.01**		**-0.01**
			(4.62)	(4.73)	(4.77)		(5.44)
BM			**0.68**	**0.67**	**0.68**		**0.69**
			(5.68)	(5.71)	(5.64)		(6.23)
Past Returns			-0.07	-0.07	-0.07		-0.14
			(0.78)	(0.85)	(0.80)		(1.84)
Analyst Experience			**0.03**	**0.03**	**0.03**		**-0.29**
			(2.65)	(2.62)	(2.86)		(2.88)
Affiliation			-0.32	-0.33	-0.32		**-0.43**
			(1.79)	(1.72)	(1.79)		(2.43)
All Star			-0.02	-0.13	-0.01		0.05
			(0.16)	(1.21)	(0.14)		(0.25)
Brokerage Size			**0.00**	**-0.00**	**-0.00**		**-0.01**
			(2.59)	(2.11)	(2.82)		(3.59)
Fixed Effect	Month	Month	Month	Month	Month	Month	Month
Fixed Effect			Indus	Indus	Indus	Analyst	Analyst

Table V: School Tie Regressions for Sell Recommendations

This table reports panel regressions of returns on sell recommendations of analysts. The dependent variable is future returns (Ret). The regressions were run daily, but coefficients have been adjusted to represent monthly returns in percent. The first 2 variables are categorical variables of whether or not the analyst is linked in an education network to the given firm on which she is making a recommendation: (i) *Linked to Mgmt* indicates the analyst is linked to the senior officers, (ii) *Linked to Either* indicates the analyst is linked to either the senior officers or the board of directors. *Top 10 Most Linked* is a categorical variable indicating if an analyst attended a school with the highest number of links to senior management (or the board of directors) in our sample. *Ivy League* is a categorical variable indicating if an analyst attended a school in the Ivy League. *US News Top 40* is a categorical variable indicating if an analyst attended a school ranked in the Top 40 National Universities in US News and World Report. *Size* is the market capitalization of the firm, *BM* is the book-to-market ratio of the firm, and *Past Returns* is the past one-year stock return of the firm. *Analyst Experience* is equal to the number of years the analyst has been making recommendations recorded in I/B/E/S. *Affiliation* is a categorical variable that measures whether or not the given firm has an underwriting relationship with the analyst s brokerage. *All Star* is a categorical variable equal to 1 if the investor was voted an all star analyst in the October issue of Institutional Investor magazine for the given year. *Brokerage Size* is the total number of analysts that work at the given analyst s brokerage house. Fixed effects for month (Month), analyst (Analyst), and industry (Indus) using the Fama-French industry definitions, are included where indicated. All standard errors are adjusted for clustering at the month level, and t-stats using these clustered standard errors are included in parentheses below the coefficient estimates. 5% statistical significance is in

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Ret	**Ret**	**Ret**	**Ret**	**Ret**	**Ret**	**Ret**
Linked to Mgmt	0.02		0.04	0.04	0.05	-0.03	-0.06
	(0.25)		(0.40)	(0.34)	(0.41)	(0.34)	(0.48)
Linked to Either		0.01					
		(0.20)					
Top 10 Most Linked			0.01				
			(0.11)				
Ivy League				-0.01			
				(0.08)			
Top 40 US News					0.02		
					(0.27)		
Size			**-0.01**	**-0.01**	**-0.01**		**-0.01**
			(3.79)	(3.82)	(3.77)		(4.66)
BM			**0.45**	**0.41**	**0.45**		**0.48**
			(3.93)	(3.40)	(3.92)		(4.45)
Past Returns			**-0.28**	**-0.35**	**-0.30**		**-0.37**
			(2.24)	(2.77)	(2.41)		(3.31)
Analyst Experience			0.02	0.02	0.02		-0.22
			(1.44)	(1.52)	(1.34)		(1.69)
Affiliation			-0.23	-0.36	-0.29		-0.27
			(0.76)	(1.06)	(0.95)		(0.83)
All Star			-0.18	-0.11	-0.18		-0.10
			(1.65)	(0.92)	(1.55)		(0.67)
Brokerage Size			0.00	0.00	0.00		0.00
			(0.86)	(0.75)	(0.94)		(0.75)
Fixed Effect	Month	Month	Month	Month	Month	Month	Month
Fixed Effect			Indus	Indus	Indus	Analyst	Analyst

Table VI: Regulation FD and Strength of Links

This table reports panel regressions of returns on buy recommendations of analysts. The dependent variable is future returns (Ret). The regressions were run daily, but coefficients have been adjusted to represent monthly returns (abnormal returns) in percent. *Linked to Mgmt* indicates the analyst is linked through an educational network to the senior officers of the firm, (ii) *Linked to Either* indicates the analyst is linked to either the senior officers or the board of directors. *Post Reg-FD* is a categorical variable equal to 1 for all recommendations made after Regulation FD came into effect (Oct 23, 2000), and 0 for all recommendations made before. *Link Mgmt*Post Reg-FD* is the interaction term between *Linked to Mgmt* and *Post Reg-FD*. *Frac Link to Analyst* is the fraction of the board of directors that is linked to the analyst. *Linked by Conf* indicates the analyst is attended a school competing in the same athletic conference as that of a senior manager. All other independent variables are described in Table V. Column 3 (Sub) includes only the subset of analysts that are in the sample both pre- and post-Reg FD. Fixed effects for month (Month), analyst (Analyst), and industry (Indus) using the Fama-French industry definitions, are included where indicated. All standard errors are adjusted for clustering at the month level, and t-stats using these clustered standard errors are included in parentheses below the coefficient estimates. 5% statistical significance is indicated in bold.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full	Full	Sub	Full	Full	Full	Full
	Ret	**Ret**	**Ret**	**Ret**	**Ret**	**Ret**	**Ret**
Linked to Mgmt	**0.79**	**0.72**	**0.88**			**0.31**	**0.31**
	(4.31)	(3.61)	(3.88)			(2.68)	(2.59)
Link Mgmt* Post-RegFD	**-0.58**	**-0.63**	**-0.91**				
	(2.51)	(2.53)	(3.03)				
Frac Link to Analyst				**0.69**	**0.57**		
				(2.62)	(2.07)		
Linked to Either					**0.19**		
					(2.43)		
Linked by Conf						**0.22**	**0.15**
						(2.59)	(1.98)
Post Reg-FD	**-0.97**	**-1.78**	**-1.82**				
	(3.68)	(3.43)	(3.56)				
Top 10	0.03					0.02	0.02
	(0.43)					(0.31)	(0.27)
Size	**-0.01**	**-0.01**	**-0.01**	**-0.01**	**-0.01**		**-0.01**
	(5.24)	(6.55)	(5.89)	(5.39)	(5.47)		(5.26)
Bm	**0.62**	**0.67**	**0.79**	**0.70**	**0.70**		**0.56**
	(4.61)	(5.58)	(5.91)	(6.24)	(6.24)		(4.35)
Past returns	**-0.19**	**-0.27**	**-0.24**	-0.14	-0.14		-0.06
	(1.94)	(3.54)	(3.01)	(1.83)	(1.83)		(0.62)
Analyst Experience	**0.03**	**0.16**	**0.17**	**-0.29**	**-0.29**		**0.03**
	(2.16)	(2.74)	(3.03)	(2.85)	(2.85)		(2.75)
Affiliation	**-0.83**	**-0.83**	**-0.80**	**-0.42**	**-0.42**		-0.31
	(3.73)	(4.31)	(3.54)	(2.40)	(2.40)		(1.72)
All Star	-0.04	0.17	0.17	0.05	0.05		-0.07
	(0.31)	(0.78)	(0.74)	(0.25)	(0.24)		(0.71)
Brokerage Size	**-0.00**	**-0.01**	**-0.01**	**-0.01**	**-0.01**		**-0.00**
	(2.30)	(4.04)	(4.17)	(3.61)	(3.62)		(2.96)
Fixed Effect	Indus	Analyst	Analyst	Analyst	Analyst	Month	Month
Fixed Effect		Indus	Indus	Month	Month		

Table VII: Regulation FD, US and UK Evidence

This table shows calendar time portfolio returns (in local currency). We classify a stock as having an educational tie to the analyst if he/she attended the same institution as a senior officer (CEO, CFO or Chairman) or a board member. Each recommendation is assigned to one of two portfolios: (1) a BUY portfolio consisting of all stocks upgraded with respect to the previous recommendation, or initiated, resumed or reiterated coverage with a buy (IBES code = 2) or strong buy (IBES code = 1) rating, and (2) a SELL portfolio, consisting of all stocks downgraded with respect to the previous recommendation, initiated, resumed or reiterated coverage with a hold (IBES code =3), sell (IBES code = 4) or strong sell (IBES code = 5) rating or dropped from coverage. If the brokerage house does not report the stock as dropped from coverage and a recommendation is not revised or reiterated within twelve months, it is considered expired. We skip a trading day between recommendation and investment (disinvestment). For the BUY portfolio each recommended stock is held until it is either downgraded, dropped from coverage, or the recommendation expires. We compute value weighted portfolios by averaging across analysts, weighting individual recommendations by the IBES recommendation code; for the BUY portfolio, we reverse these recommendation codes so that a strong buy is set to 5 and a strong sell is set to 1. The SELL portfolio is constructed in a similar fashion with the exception that that the original IBES recommendation codes (i.e., strong sell=5, and strong buy=1) are used as portfolio weight. Panel A presents average returns on US stocks for two subperiods, Pre- and Post-REG FD, corresponding to returns for recommendations issued prior and subsequent to the introduction of Regulation FD in the US on October 23, 2000. Panel B presents average returns and DGTW-adjusted returns in the period 1993 to 2006 for UK stocks; DGTW characteristic-adjusted returns are defined as raw returns minus the returns on a value weighted portfolio of all I/B/E/S firms traded in the UK in the same size, (industry-adjusted) market-book, and 1-year momentum quintile. Analogous to our US sample, we collect educational data on I/B/E/S analysts issuing recommendations on stocks traded in the UK, as defined by the I/B/E/S country exchange code. We hand matched firms from the Boardex sample to I/B/E/S using company names. Daily returns (in local currency) are from Factset. Panel C presents average returns on UK stocks for two subperiods, Pre- and Post-REG FD, corresponding to returns for recommendations issued prior and subsequent to the introduction of Regulation FD in the US on October 23, 2000. Returns are in monthly percent. L/S is average return of a zero cost portfolio that holds the portfolio of linked stocks and sells short the portfolio of non-linked stocks. t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold.

Panel A: US Pre/Post- REG FD	Buy recommendations						Sell recommendations					
	Pre REG FD		Post REG FD		Difference		Pre REG FD		Post REG FD		Difference	
No shared educational background	1.25		0.76		0.50		0.92		1.18		-0.26	
	(1.93)	L/S	(0.87)	L/S	(0.46)	L/S	(1.57)	L/S	(1.12)	L/S	-(0.23)	L/S
Analyst linked to senior	**2.03**	**0.78**	1.02	0.26	1.01	0.51	**1.20**	0.29	0.97	-0.21	0.24	0.50
Management	(3.12)	(3.50)	(1.19)	(1.51)	(0.95)	(1.73)	(1.99)	(1.31)	(1.00)	-(1.08)	(0.22)	(1.65)
Analyst linked to senior	**1.94**	**0.68**	0.90	0.14	1.04	**0.55**	1.07	0.16	1.09	-0.09	-0.01	0.25
Management or board of directors	(3.12)	(4.36)	(1.05)	(0.84)	(1.01)	(2.38)	(1.87)	(1.12)	(1.16)	-(0.53)	-(0.01)	(1.13)

Table VII: Regulation FD, US and UK Evidence (continued)

Panel B: UK Sample 1993-2006	Buy recommendations						Sell recommendations					
	Raw returns				Abnormal returns			Raw returns			Abnormal returns	
No shared educational background	0.71				-0.13			0.45			-0.24	
	(1.41)	L/S			-(0.51)	L/S		(0.78)	L/S		-(0.91)	L/S
Analyst linked to senior Management	**2.58**	**1.87**			**1.54**	**1.67**		-0.34	-0.79		0.02	0.26
	(3.11)	(2.79)			(2.09)	(2.20)		-(0.39)	-(1.06)		(0.04)	(0.46)
Panel C: UK Pre/Post- REG FD	Pre REG FD		Post REG FD		Difference		Pre REG FD		Post REG FD		Difference	
No shared educational background	0.54		0.91		-0.37		0.38		0.57		-0.19	
	(0.71)	L/S	(1.47)	L/S	-(0.36)	L/S	(0.47)	L/S	(0.80)	L/S	-(0.16)	L/S
Analyst linked to senior management	**2.32**	**1.78**	**2.90**	1.99	-0.58	-0.21	-0.48	-0.86	-0.08	-0.65	-0.41	-0.21
	(1.98)	(2.11)	(2.48)	(1.82)	-(0.34)	-(0.15)	-(0.52)	-(1.18)	-(0.04)	-(0.40)	-(0.23)	-(0.14)

Figure 1: XYZ Corp

This figure shows actual total returns of the XYZ Corp. (anonymized name and dates) around the upgrade by a linked analyst, as well as the return on its corresponding risk-adjusted benchmark.