Politically-Connected Analysts

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Abstract:

This paper evaluates the advantages of being a politically-connected equity analyst, i.e., an analyst that makes large political donations. I find that these politically connected analysts are more accurate than other small donor and non-donor analysts, and they actually become more accurate after they become large donors, suggesting their enhanced performance derives from an advantage gained through their political activity. These results are stronger when (i) the analyst works or lives in the state represented by the benefitting politician, (ii) the covered firms are economically connected to the government, and (iii) the benefitting politician serves on a committee that regulates the covered firm. Overall, these results suggest that politically-connected analysts benefit from relationships with politicians who possess knowledge that impacts firms' prospects.

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1. Introduction

In November 2011, a CBS '60 Minutes' report detailed extensive insider trading by members of congress around information on Medicare drug reimbursement changes, the actions of congressional committees, and coming actions by the Treasury Department and Federal Reserve. The CBS report highlights the importance of political intelligence to institutional investors. By some estimates, hedge funds and other institutional investors spend more than $400 million per year on gathering political intelligence, and the information generated is now a major source of alpha for these investors.[1] In April 2012, the US government passed into law the Stop Insider Trading on Congressional Knowledge (STOCK) Act. This legislation was designed to stop congressional insiders from using material non-public information to trade stocks for personal profit, a practice that attract considerable attention during the financial crisis.[2]

Yet, while the STOCK Act made insider trading by members of congress illegal for the first time, it is primarily focused on preventing trading by members of congress. It does not explicitly bar politicians from passing information to analysts, but instead requires a study by the Comptroller General of the United States on the political intelligence industry by April 2013 (12 months from the date of the Act's passage). This study by the Comptroller is required to examine "the legal and ethical issues that may be raised by the sale of political intelligence".[3] There is a significant ongoing debate in the legal field over the political intelligence industry and its legal legitimacy (Nagy and Painter, 2012; Kim, 2012; Bainbridge, 2012).

One interpretation of this legislative language is that current statutes do not prohibit politicians or their staffers from passing information to outside third parties. Indeed nowhere else

[1] See "Buying Political Intelligence Can Pay Off Big for Wall Street", The Wall Street Journal, January 18, 2013

[2] See for example, 'The Congress Insider Trading Scandal is Outrageous' by Henry Blodget of *Business Insider*, Nov 14, 2011 and 'Durbin Invests With Buffet After Funds Sale Amid Market Plunge', by James Rowley of Bloomberg, June 13, 2009.

[3] See http://www.gpo.gov/fdsys/pkg/PLAW-112publ105/html/PLAW-112publ105.htm for the complete text of the STOCK Act

in the law is political intelligence or the passage of information from Congressional insiders to others mentioned. This suggests information could be legally used by outside parties in at least two different ways; (1) the information could be used for stock trading as part of a "mosaic" of public and private information (which is allowed under current insider trading laws)[4], or (2) the information could be disseminated publicly by the recipient. In this paper, I investigate this latter scenario; specifically, do stock analysts obtain relevant information from political insiders and then use this information to improve earnings forecasts on firms they cover?

I examine whether sell-side analysts at brokerage firms issue more accurate earnings forecasts when they have ties to political insiders. I use political donations by analysts as a proxy for determining which analysts have a relationship with political insiders. Based on personal donations by the analyst to politicians or their proxy political action committees (PACs), I am able to identify those analysts who may have a relationship with a politician that yields valuable information for the analyst.

Overall, I show that "large donor" analysts (in the top 5% of all contributions in any given year) are more accurate than other analysts. These results hold after accounting for analyst fixed effects, covered firm fixed effects, analyst characteristics, covered firm characteristics, and a variety of other control variables. In fact, an analyst becomes more accurate in the year he first becomes a big donor.

I conduct additional tests to explore the connection between analysts and politicians. I find that an analyst's accuracy is positively related to the closeness in time between the analyst's political donation, and the release of his quarterly earnings estimates. Further, analysts are more accurate when they work or live in the state represented by the politician that benefits most from

[4] The CFA Institute recognizes Mosaic Theory as a legal means of stock analysis using a combination of immaterial inside information and publicly available information. Various business dictionary provide a definition for the term including the following: http://www.businessdictionary.com/definition/mosaic-theory.html

the analyst's donation, as well as when the politician serves on a committee that regulates the firm being covered by the analyst. Finally, earnings estimates by large donors are more accurate when the covered firm has a connection to the government either through a business relationship (i.e. the government is a major customer of the firm), or the government closely regulates the firm's industry.

To my knowledge, this paper is the first to show empirical evidence of the role analysts play in gathering political intelligence. I show that this information is valuable and important when making firm specific earnings forecasts. The role of analysts in gathering this information is particularly noteworthy in a post Reg-FD world, when most relevant firm specific information is widely disseminated via the internet, and analyst research departments are struggling to justify their existence as a cost center at many brokerages (Green, Jame, Markov, and Subasi 2012). This work suggests that analysts are especially valuable when they have access to private information and they can connect investors and insiders, either directly or indirectly. Political intelligence is one example of how analysts can continue to gather unique information for investors, but there are likely other opportunities they can exploit as well.

There are three current lines of research that are closely aligned with this paper. The first deals with the impact of corporate political donations, and demonstrates how firms can benefit themselves and their shareholders through donations (for example, Cooper, Gulen, and Ovtchinnikov, 2010; Correia, 2012; Duchin and Sosyura, 2012). These benefits can be through a form of regulatory capture, or through special interest benefits conveyed by congress. This paper demonstrates how information about the special benefits granted to some firms (or penalties to competitors of favored firm) can be conveyed to markets through analysts.

The second related line of the literature deals with how individuals use political donations to maximize their own well being. Broadly individuals act within their own best interest when making political donations rather than acting based on political ideology that might be detrimental to their own economic well-being (for example, Ovtchinnikov and Pantaleoni, 2012; Belo, Gala, and Li, 2013. This behavior enables the analyst to gain information which benefits themselves and their clients without regard for personal political convictions.

The third related line of literature deals with how investors behave based on the political climate and the actions of firms. Here, the paper that is most similar to mine is Jiang, Kumar, and Law, 2012. They also examine equity analysts and political behavior, but through the lens of political affiliation. They show that Republican equity analysts are more cautious in incorporating new information into their earnings forecasts, and in making new recommendations. Overall, their conclusion is that Republican equity analysts are more conservative in their professional roles as analysts compared with their peers. In contrast, I examine whether large political donations are associated with greater accuracy regardless of political affiliation with a particular focus on which channel any associated effects operate through. Thus, while our papers are related, their focus is on the effect of a specific personal characteristic (political leanings); my focus is on a novel way in which analysts provide value, and the source of that value. Other work in this area includes Bonaparte, Kumar, and Page (2012), Hong and Kostovetsky (2011), and Chin and Parwada (2010).

The rest of the paper is organized as follows: Section 2 covers background literature in greater detail and then sets out my hypotheses based on this literature. Section 3 deals with data and methodology, Section 4 examines the results, Section 5 discusses robustness checks and additional tests performed, while Section 6 concludes.

2. The Setting and Hypotheses

Essentially there are two questions of interest in this paper. First, are politically active analysts more accurate? If so, then are the analysts more accurate because they receive direct information from politicians, or because political activism proxies for an unobservable factor? One example of such an unobservable is attention to financial news. Bonaparte and Kumar (2012) examine whether politically active people have greater exposure to financial news, and find that regardless of political affiliation, politically active individuals are 9-25% more likely to participate in the stock market. My work builds on this by proposing that perhaps politically active big donor analysts pay more attention to news and the actions of Washington DC, and this may lead these analysts to have more accurate earnings estimates than their politically inactive peers.

There is substantial support in the literature for the notion that political views impact investment decisions. For example, Bonaparte, Kumar, and Page (2012) show that investors' attitudes towards the markets are influenced by the political atmosphere in Washington. Hong and Kostovetsky (2011) show that mutual fund managers who make campaign donations to Democrats hold less of their portfolios in companies that are deemed socially irresponsible, while Chin and Parwada (2010) show that Republican (Democratic) institutional investors during the 2000 election were overweight on stocks that were most likely to benefit from a Bush (Gore) presidency. Hutton, Jiang and Kumar (2013) find that firms with Republican managers take on less risk in their professional capacities as managers. Christensen, Dhaliwal, Boivie, and Graffin (2012) find similar effects related to manager political views and corporate tax policies, and Hutton, Jiang and Kumar (2012) find that corporate misconduct is related to managerial political views.

However, there is also a large body of evidence that political donors, both corporations and individuals, receive direct benefits from recipient politicians. Cooper, Gulen, and Ovtchinnikov (2010) show that political donations by firms are associated with larger future returns. Their results are important to my paper in that they show that even relatively small sums of money from individual firm donations can influence the behavior of politicians. Similarly, Mian, Sufi, and Trebbi (2012) show that subprime lenders and borrowers influenced congressional voting decisions in the time period leading up to the financial crisis. Kim, Pantzalis, and Park (2012) show firms in geographic areas that exert considerable political influence have higher stock returns than firms in areas with lower levels of political influences. Correia (2012) finds politically connected firms are less likely to be involved in an SEC enforcement action and face lower penalties on average, and these firms increase their expenditures during the periods when they are misreporting information to investors. Boubakri, Guedhami, Mishra, and Saffar (2012) find that politically connected firms enjoy a lower cost of equity capital than their non-connected peers. In sum, these papers provide the basis for my hypothesis that analysts associated with large donations to politicians may receive beneficial information directly from the politicians.

The view that political donations are beneficial to the donor is contentious however, and other authors have come to different conclusions about the usefulness of corporate donations on firm value. Aggarwal, Meschke, and Wang (2012) find that political donor corporations have lower free cash flows and lower returns. In a similar vein, using data from 31 countries, Boubakri, El Ghoul, and Saffar (2012) show that politically connected firms exhibit acute agency problems, and hold more cash than non-connected peers. Faccio (2010) examines evidence from firms in 47 countries and shows that companies with political connections have higher leverage,

and underperform compared to nonconnected companies. Duchin and Sosyura (2012) show that politically connected firms were more likely to receive TARP funds during the 2008 financial crisis, yet investments in these politically connected firms underperformed investments in the unconnected firms.

Regardless, of which view of the usefulness of corporate donations is correct, there is evidence that donations impact the donor, and thus it is conceivable that a donor analyst might receive valuable information. Based on the past work in this literature, two conclusions which are important to my work emerge. First, political donations do influence politicians such that firms receive benefits; whether these benefits are commensurate with their spending is an ongoing debate. Second, political leanings of the analyst and the political situation in Washington influence analyst behavior.

Given this, I combine these two sets of findings and hypothesize that similar to firms receiving benefits from making significant donations to political candidates, analysts donating large amounts of money will also benefit. Just as the influence of political donations on firm returns is debated in the literature, it is also debatable whether politically active analysts will be more or less accurate than non-political analysts. I hypothesize that whatever benefits, large or small, an analyst might gain from political connectedness, only those analysts who are making substantial contributions will receive any benefits. If there are benefits to being politically connected as an analyst, it makes sense that these benefits would accrue to the most connected analysts who have given the largest contributions to politicians. This leads to Hypothesis 1.

Hypothesis 1: Analysts that make large political donations will have more accurate earnings estimates than other analysts.

The expected channel for this hypothesis could be as result of: (1) a valuable information conduit from politicians to analysts, or (2) an indicator of unobservable analyst skill and accurate worldview which enables these analysts to more accurately estimate earnings (e.g. an intuitive understanding of how political machinations are likely to be resolved). The information conduit hypothesis makes sense in the context of the evidence on individual political contributions provided by Ovtchinnikov and Pantaleoni (2012), while the idea of political donations being correlated with unobservable analyst skill fits with the results of Bonaparte and Kumar (2012).

An information conduit between analysts and politicians could be a result of an informal exchange of donations from the analyst (and perhaps others at his brokerage firm) in return for useful political intelligence. Alternatively, it could also be the result of an ongoing social relationship between the analyst in question and the politician. This relationship need not be based on donations or the passing of political intelligence. Instead, both might be byproducts of an existing friendship between two individuals. For example, Representative Smith may give Analyst Jones political intelligence in passing while the two play golf, and because they are friends, Analyst Jones may be a regular donor to Representative Smith's campaign. Assuming analysts do have an information conduit to Washington politicians, it is difficult to determine whether that information flow is due to a "cash for information" channel or a "friendship for information" channel, or a combination of the two.

Cohen and Malloy (2010) provide the basis for the view that social links and friendship between analysts and politicians may enable the passing of political intelligence. They show that personal connections among politicians have a significant impact on legislative voting behavior. If social association between politicians is enough to influence voting behavior, then it seems likely that social interactions may also be sufficient to allow information sharing between

government officials and private sector analysts. Aslan and Grinstein (2012) provide further support for this notion showing that CEOs generate political rents by socializing with politicians. These associations improve the CEOs compensation and increase the firm's operating performance. Kostovetsky (2010) finds similar important benefits to firms having politically connected board members during the 2008 financial crisis.

In contrast to the view that information might pass to analysts as a result of friendship with politicians, some past work has shown that political donations are made primarily for the purpose of gaining short term benefits. This type of action by analysts is consistent with a "campaign contributions for information" style relationship. Hersch, Netter and Pope (2008) find that political contributions are made by firms in order to take advantage of short term opportunities, and not as a means of building long-term political capital. Ovtchinnikov and Pantaleoni (2012) show that individuals make political contributions with strategic objectives in mind, particularly by targeting politicians with power to provide economic benefits to the individual. Garner, Kim, and Yore (2012) and Belo, Gala, and Li (2013) both find further evidence that allegiance to a particular political party and long standing relationships with certain politicians are not as important as having ties to the politicians in power at any given time.

In this paper, I restrict myself to analyzing whether any increased accuracy by *Big Donor* analysts is due to a politician-analyst information conduit, or if it is due to political donations being correlated with increased unobservable skill as an analyst. I term these two channels "information conduit" and "unobservable skill" going forward. I examine evidence on these channels beginning in Table IV.

Assuming that *Big Donor* analysts are more accurate than other analysts, then regardless of which of the channels (information conduit or unobservable skill) is correct, it is likely that a

stronger connection between the government and the target firm (firm who earnings are being estimated) will result in more accurate *Big Donor* analyst estimates. Evidence on this is provided by Cohen, Coval and Malloy (2010) who show that changes in the leadership of congressional committees have a dramatic influence on the success of firms that are economically linked to the actions of the committee in question. Thus if the information conduit is responsible for any improvement in analyst earnings estimates, then it is likely a politician will have more information about a firm that is connected with the government. Similarly, an unobservable skill correlated with political activity is likely to be stronger if that firm has a deeper connection to the government. This leads to hypothesis 2.

Hypothesis 2: Analysts who are Big Donors will be more accurate when covering firms that have a connection to the government either as a supplier or a highly regulated firm.

Assuming support is found for hypothesis 1 and 2, this would suggest with reasonable confidence that analysts making significant donations are more accurate than other analysts. So, assuming this holds, the next step is to look for evidence surrounding which of the two channels is responsible for the improved accuracy. This leads to hypotheses 3 and 4.

Hypothesis 3: Big Donors will become more accurate in their predictions as the time between donation and analyst estimate forecast decreases.

If an information conduit channel between politicians and analysts exists and is identifiable through political donations, then the strength of this information channel is likely to be highly dependent on the time between a donation and the analyst's estimate. Essentially, analysts who receive information (e.g. information on the strength of new regulations hitting the

industry, a regulatory decision from a body such as the FDA, etc.) from politicians that improve analyst estimates are probably making donations to politicians in relatively close proximity to when they are making donations. This would be true either if a cash for information style transaction is being conducted, or if a politician and analyst are close friends. It is unlikely that an analyst would receive information based on a donation or a friendship from 3 years earlier for example. Thus if improve analyst estimates are driven by information flow from politicians, the improvement should be significantly related to the time between the donation and when the analyst receives the information. Further, since analysts have an incentive to put this information out as early as possible to help their clients and beat other analysts, it is likely that the time between an analyst receiving information, and publishing an estimate is brief. For this reason, I include the absolute value of the time between an analyst's donation and their estimate as a control variable.

In contrast, if analyst donations are merely a proxy for an unobservable skill based on political interest which makes analysts better at predicting firm earnings, then it is unlikely that there would be a significant relationship between the time interval in an analyst donation and estimate, and the accuracy of that estimate. Thus, I interpret significance on this variable as evidence in favor of the information conduit channel. That said, evidence in favor of the information conduit channel does not rule out effects from the unobservable skill channel – it is entirely possible that both channels may operate simultaneously. This would in fact be consistent in some respects with the past literature which has shown differing value for political donations depending on the circumstances surrounding the donations (Aslan and Grinstein (2012)). I test hypothesis 3 beginning in Table IV.

Hypothesis 4: Big Donors with a geographic link to a politician will be more accurate than analysts who have no obvious geographic link to the politician receiving the donation.

Information flow between politicians and analysts is likely to be significantly easier if the politician represents the state in which the analyst lives and works. This type of geographic link would facilitate meetings and make a friendship between the two considerably more likely. In contrast, increased accuracy driven by unobservable skill related to political interest is unlikely to be affected by geographic proximity between the analyst and the politician. Therefore, I include a binary variable for analysts making significant donations to politicians in the same state. I interpret positive significance on this coefficient as evidence in favor of the information conduit channel over the unobservable skill channel. Again, it is important to be clear that both channels may be in operation simultaneously.

3. Data and Methodology

This paper requires data on analysts' political donations. This data can be obtained from the Federal Election Commission (FEC) filings on the political contributions of all US citizens to all political candidates and political action committees from January 1992 through November 2012. These data are restricted to donations of $100 or more and include donations to all candidates and PACs at all levels of federal elections. Although it requires a substantial amount of hand collection, using data directly from the FEC filings results in substantially more complete data than alternative sources that some past authors have relied on.

I classify candidates and PACs as Republican, Democrat, or Independent based on the FEC filings and data gathered online by hand and with a web crawler. I also gather data from IBES on analyst earnings estimates. These data include all earnings estimates for all analysts from 1992 to 2012. I allow only one earnings estimate per analyst per firm per quarter by

dropping all estimates that occur before the analyst's last one for a given company in a given quarter. The purpose in doing this is to remove stale earnings estimates since many analysts will update their estimates multiple times over the course of a quarter. I use the IBES master names file to match the name of each analyst with the indentifying code in IBES which is linked to the analyst's past estimates. I then combine the FEC donations data with the IBES estimates data using a name and firm matching algorithm. This matches the two datasets based on the name of the donor in the FEC database and his reported employer with the analyst name in the IBES names database. I supplement data in the names file with information gathered off of the internet including the brokerage firm of the analyst. I check all of the algorithm's matches by hand for a final matched sample of 46,968 analyst contributions. For robustness, I also remove all donors that do not report their occupation to the FEC as being related to equity research (e.g. equity analyst, banker, analyst, etc.), and those where the donor is not located in the same state as his brokerage firm's headquarters. My results are unchanged by these additional screens, but I do not use them in my standard tests because the occupation variable is optional for FEC reporting, and many of the donors do not report their specific occupation as a result. The effect of using these screens would be to shrink my sample dramatically and limit my ability to perform certain tests with fixed effects due to a lack of time series observations. The results using these screens are not included in this text, but are available from the author upon request.

Data on government connections with firms are based on the Compustat segments data and industry codes from Compustat. In the segments data, if the government is listed as a customer consuming more than 10% of the firms sales, then I classify the firm as having a government connection. Similarly, I classify a firm as having a government connection if the firm is in a regulated industry including tobacco and alcohol, financials and insurance, utilities,

telecom, pharmaceuticals, healthcare, autos (for the period 2008-2012), mining, or oil exploration.

My general methodology throughout the paper is pooled OLS regressions with various fixed effects included in many cases. I also use a difference-in-differences approach to examine the effects of becoming a political donor on analysts versus a pool of three other matched analysts all covering the same firm. The matching procedure matches analysts based on minimizing the sum of squared percentage differences of two factors: number of days between earnings announcement and analyst estimate (*DaysBefore)* and the analyst's experience as measured by the length of time (in quarters) the analyst is in the dataset (*Analyst Tenure*). The results in this difference-in-differences test are robust overall to using a propensity matching criteria based on a probit regression of analyst accuracy and all other variables. However, I use the minimized sum of squares procedure as the baseline because my primary concern in this test is to show that *Big Donor* analysts with comparable experience to other analysts making estimates at the same time are more accurate. As such inclusion of other control variables in a propensity score matching system only serves to potentially offset the importance of analyst experience and time to earnings announcement in the matching process. The results using a propensity score matching methodology are available from the author upon request.

4. Results

I begin by examining the donation statistics for my sample. As Table I reveals, there are 46,968 individual contributions by analysts during the period 1992-2012. These contributions are spread across 1,789 analysts and 326 firms, which yields a total of 111,634 quarterly earnings estimates for a given firm by analysts who are donors. Roughly 19% of analysts are donors.

The average contribution for all contributors (analysts and non-analysts) is $944, while the 95th percentile is $2400 and median is $400. There are 44,259 firm-quarter observations with an earnings estimate by a past or future big donor.

The mean contribution by analysts is roughly $1,416 each year, but there is considerable variation in these donations with analysts in the top 5% of all donors donating an average of $5,500 each year. Total contributions by all analysts at a given firm have a mean of $18,777 a year, with total donations by analysts alone at the 95th percentile of firms each year giving in excess of $128,000 on average. Based on these data, I classify analysts in the top 5% of all donors each year as being "Big Donors". These big donor analysts are identified with a binary variable in all tests and tables going forward.

An analyst may move in and out of the *Big Donor* category each year based on their own contributions and what the 5% cutoff is each year. Predictably, this cutoff increases consistently between 1992 and 2012. In my tests, I identify analysts who give enough to fall into the *Big Donor* category as those analysts most likely to gain an advantage from political relationships. I do not claim that all of these analysts gain advantage from their donations, nor do I claim that none of those analysts not in the *Big Donor* category may have any politically based advantages. Instead, the *Big Donor* category is merely a convenient threshold to identify the analysts most likely to have political connections. My results are robust to the use of a top 1% threshold for big donors instead.

Throughout most tests, I use the *Big Donor* category rather than simple level of donations because of non-linearity in the effect of donations. It is unlikely that somewhat donating $10,000 has precisely twice the political advantage as someone donating $5,000 and ten times the advantage of someone donating $1,000. Instead, it seems more likely that up to some certain

threshold, donations buy a donor no political advantage, and beyond this threshold, they buy increasing amounts of advantage. I examine this assumption in Table VIII and find support for it. Given that the average House Representative who won an election raised $1.4 million in 2012, and considerably less in earlier years, even a single donation of $5,000 is a significant help in meeting fundraising goals.

[Insert Table I here]

Table II provides descriptive statistics on control variables and earnings accuracy for the sample of analysts and the firms they cover. Panel A shows variables based on all analysts and the firms they cover regardless of whether they make any kind of donation during the sample period, while Panel B examines only those analysts falling into the big donor category. Panel C examines analysts at firms that are politically active and significantly aligned with one party or the other. I refer to these firms as *Partisan Firms* and define them as firms where at least 66% of all donations are made to one party.

Panel A reveals that over the sample of roughly 450,000 analyst-firm-quarter observations, the mean analyst price scale accuracy (PSA) is 0.17. This measure is defined as the absolute value of (earnings estimate – actual earnings)/firm share price. Thus when dealing with PSA, lower numbers indicate greater accuracy, and a perfectly accurate estimate would have a PSA of 0. The average earnings estimate is made roughly 19 calendar days (0.66 months) before the earnings are announced. 21% of all analysts are classified as *donors*, while approximately 1% of all analysts (5% of donors) are classified as *Big Donors*. An analyst who is a big donor is also a donor. Thus the interpretation of *Big Donor* is that it is the marginal effect over and above simply being a donor from donating a large amount. Roughly 25% of all firms are classified as having a government connection (*Gov't Connection*) as a result of the criteria detailed above.

Panel B shows that analysts classified as *Big Donors* in a given year, make more accurate estimates in that year based on PSA than other analysts. *Big Donors* are also more likely to fall into the upper half of the accuracy distribution as evidences by the *Above Median Accuracy* variable. Panel B shows that 62% of big donors fall above the median in the distribution of earnings estimate accuracy. *Geographic Connection* measures whether or not an analyst works in the same state that the largest recipient of the analyst's donations represents. The table shows that this connection exists for 64% of big donor analysts. Similarly *Committee Connection* measures whether or not the politician receiving the largest donation from an analyst in a given year sits on a committee that regulates a target firm covered by the analyst. 41% of big donor analysts and donation recipients have this connection. Further, while only 2% of all firms covered by analysts have government connections, 36% of those covered by big donors have political connections.

Finally, Panel C shows that analysts working for partisan firms are about as accurate as other analysts, but while only 1% of the overall analyst population is a big donor, a full 5% of analysts at partisan firms are big donors. Overall, 48% of analysts at partisan firms are donors compared with 21% of analysts in the overall population.

[Insert Table II here]

Table III details the correlation coefficients between various control variables. The table shows that big donors are significantly correlated with greater accuracy (lower levels of PSA, and higher levels of Above Median Accuracy, both of which correspond to greater accuracy overall). The table also shows that big donors are significantly positively correlated with target firms having a connection with the government (*Gov't Connection*) and with firms having a higher market-to-book value (*Ln(M/B)*), which is often regarded as a proxy for growth

opportunities of the firm. (Here book value is the value of the firm's tangible assets less its liabilities.) The other control variables often share some significant correlation, but not to the degree that multicolinearity is likely to be a major concern in multivariate analysis.

[Insert Table III here]

Table IV begins my main multivariate analysis. Columns 1 and 2 show that big donors are more accurate than non-donors after controlling for quarters, years, analyst tenure, firm characteristics, and a variety of other effects. In column 1, the negative and statistically significant coefficient on *Big Donor* indicates that when measured by PSA, big donors are more accurate. In column 2, this same conclusion holds with the positive and statistically significant coefficient that shows big donors are 9.1% more likely to have an above average level of accuracy after controlling for other factors. This evidence is in support of hypothesis 1 -- it appears that big donors make more accurate earnings estimates than other analysts.

Column 3 and 4 examine these same accuracy measures regressed on *Big Donor* and other control, after accounting for the time interval between the donation by the analyst and his estimate release. Columns 3 and 4 also account for partisan leanings of the firm and the control of congress. Once gain the results show that big donors are more accurate. *Big Donor* is negative and significant in Column 3 where *PSA* is the dependent variable and it is positive and significant in Column 4 where *Above Median Accuracy* is the dependent variable. These effects hold after accounting for the time interval between donations and earnings estimate releases (*Days-to-Donation*). In Table IV, I account for this time interval using a series of dummy variables so that all observations may be included. If I used the actual number of days in the time interval, any non-donor would have dropped out of the regression. The omitted binary variable in Table IV is time between donation and estimate greater than 360 days. As such the interpretation

on all of these coefficients is how much more accurate a big donor when the donation falls within each given time interval in comparison with a donation 360+ days ago. The statistically significant coefficients suggest that the time interval between donation and estimate does matter, and the effect of the donation is stronger the more recent it is. This is evidence in favor of Hypotheses 1 and 3.

Columns 3 and 4 also provide evidence in support of Hypothesis 2. The coefficient on the interaction between *Big Donor* and *Gov't Connection* is statistically significant, and the direction (negative in Column 3, positive in Column 4) indicates that when big donors are making estimates on the earnings of firms with a government connection, they are more accurate than they are when making estimates on firms without such a connection. Columns 5 and 6 show similar evidence on all of these hypotheses, but this time using firm fixed effects instead of year dummies. Interestingly, smaller donors are no more accurate than non-donors, and there is some evidence in Columns 3 and 4, that they may be slightly less accurate, which I speculate is perhaps because in some cases they may allow their political views to influence their estimates. Examining this supposition is beyond the scope of the current paper however.

Panel B of Table IV examines only big donors and those who were big donors in past years. (Thus the number of observations is larger than that for only big donor years.) The table includes a series of fixed effects including firm, year, and brokerage firm effects. This time, since only a subsample of analysts who are or were big donors is being investigated, the level of number of *days to donation* is used. Again, the coefficients suggest evidence in favor of Hypotheses 1 and 3. The coefficients on *Big Donor* (as distinguished from those who were big donors in the past, but are no longer big donors) is significant and the direction indicates greater accuracy (negative for Column 1 with *PSA* as the dependent variable, and positive for Column 2

with *Above Median Accuracy* as the dependent variable). Similarly, the coefficient on *Days-to-Donation* indicates that it has a positive statistically significant association with greater accuracy. There is also weak evidence also in support of Hypothesis 2 with the coefficient on the interaction of government connection and big donor being weakly significant and indicating greater accuracy in Column 2, but not quite significant in Column 1.

Overall, the conclusion from Table IV is that big donor analysts appear to be more accurate, and this accuracy is stronger when the time interval between a donation and the analyst estimate is small. This latter fact is evidence in favor of the information conduit channel of analyst accuracy.

[Insert Table IV here]

In Table V, I examine the effect of political donations on analyst accuracy after controlling for analyst fixed effects. In essence, this lets us interpret the coefficient on *Big* Donor as the effect on a specific analyst of becoming a big donor. This specification therefore controls for any unobservable analyst characteristics, and is a direct test of the unobservable skill channel versus the information conduit channel. If some analysts have specific personality characteristics that make them better able to intuitively understand the political process and how it will impact target firm earnings, then it is likely that these effects are largely time-invariant. However, even if the effects do vary with time, as long as their development does not correspond closely to the choice to donate to a politician, then a regression using analyst fixed effects and a big donor dummy should be able to provide evidence for or against this channel.

Table V shows that analysts become more accurate in the years they are classified as a big donor as evidenced by the statistically significant coefficients on *Big Donor* in Columns 1 and 2 which are negative and positive respectively both indicating greater accuracy.

Additionally, the binary variables for *Days-to-Donation* are also statistically significant. Again, the omitted binary variable is for those analysts making donations 360+ days ago meaning that the other variables are interpreted against that standard. The table shows that as the time interval between donation and estimate shrinks, each specific analyst becomes more accurate compared with past estimates by that same analyst. I view this as compelling evidence in favor of the information conduit channel. Of course, this does not necessarily mean that the unobservable skill channel isn't contributing to the broader result that big donor analysts are more accurate, but it does suggest that this channel is not the predominate driver. It is also strong evidence in support of Hypothesis 3.

Table V also provides some evidence in support of Hypothesis 2. The interaction term between government connected firms and big donors is strongly statistically significant in both Columns 1 and 2, and the direction of the coefficients suggests indicates that the average big donor analyst is more accurate when he is estimating the earnings of a government connected firm in comparison to non-government connected firms. This is consistent with information flow to the analyst improving his estimates compared with estimates about other firms with less connection to the government.

[Insert Table V here]

In Table VI, I examine the connection between analyst estimates and political donations with target firm fixed effects, and controlling for the links between the donor recipient and either the analyst or the target firm. In Columns 1 through 4, once again the *Big Donor* coefficients are statistically significant and indicate greater accuracy by big donors even after controlling for target firm industry, and geographic (i.e. state) effects.

In Columns 1 and 2, I examine the effect of making donations to a congressman who sits on a committee that regulates the industry in which one of the analyst's target firms operates. Given that these congressmen sit on the committee supervising the industry of the target firm, they will certainly have relevant information that would impact the firm and its earnings going forward. As a result, if an analyst can establish a connection and information flow with that congressman, then they will have superior information regarding future earnings. Thus the *Committee-Link* variable is an important indicator for whether information is flowing to analysts from congressional politicians who have very specific and valuable information. As the table shows, *Committee-Link* is statistically significant, and the negative and positive coefficients in Columns 1 and 2 respectively indicate that analysts are more accurate when they are big donors to committee members regulating target firms of the analyst

In addition, I now examine the effect of a geographic link between analyst and donor recipient. This geographic link is a binary variable equal to 1 if the analyst works in the state that the donor recipient represents in congress. The interpretation on this coefficient is the marginal effect of a big donor analyst being geographically linked to the donor recipient in question. This is a potentially important effect because a geographic link between the two makes it much more plausible that the politician socializes (e.g. plays golf) with the analyst. Thus the presence of geographic link is probably an important prerequisite to information sharing through a friendship for information style channel.

Columns 3 and 4 show that the coefficients on *geographic link* are highly statistically significant, and the direction of these coefficients are such that geographic links appear to improve big donor accuracy measurably. This is evidence that geographic proximity is an important contributor to the *Big Donor* improved accuracy effect in support of Hypothesis 4.

However, it is not necessarily evidence against unobservable skill channel, and as noted previously, it is entirely possible that both channels are playing a role.

[Insert Table VI here]

Table VII is a difference-in-differences regression around an analyst becoming a big donor. The specification matches analysts to other analysts covering the same target firm based on the level of experience of those analysts (as measured by the number of quarters of estimates in the data), and the number of days before the actual earnings announcement that the earnings estimate is made. I measure the difference in accuracy between an analyst who will become a big donor, and his closest peer (in terms of experience and number of days between estimate and earnings release), and then examine the difference between these same two analysts after one of them becomes a big donor. If there are no peer analysts with at least 80% of the experience of the big donor making an earnings estimate within 15 days of the big donor, then the observation is dropped. This is done to be conservative with the matching, and the results are stronger when weaker matching requirements are used.

The difference between these two differences is then regressed on big donor, a dummy for All Star analysts, a dummy for analysts working a bulge bracket firm, and a dummy for government supplier (which is essentially the interaction term since all observations include a big donor). The negative and significant and positive and significant coefficients in Columns 1 and 2 respectively suggest that becoming a big donor is associated with greater accuracy compared with peer analysts and the analyst's own prior performance. This effect is stronger when the firm being examined is a government supplier. Overall, the results show that analysts are more accurate after becoming big donors compared to peer analysts.

[Insert Table VII here]

Table VIII examines the effect of donations on analyst accuracy without using the big donor context. Instead, I break up analysts based on the quartile into which their donations fall, and then examine how these donations impact their accuracy. Each quartile variable in the table is a binary variable equal to 1 or 0. Quartile 4 is omitted. Quartile 1 includes those analysts making the largest donations, while quartile 4 is the quartile for the lowest donations. (Non-donors have a zero for all 4 quartile variables and this are effectively lumped in with the quartile 4 analysts.) The results show that all of the statistically significant increase in accuracy is isolated in the top quartile of donors. The increase in accuracy is not particularly statistically strong even in this top quartile suggesting that it the effects are probably isolated to the higher level donors within this group. The lower level quartiles do not display any statistical significance compared with non-donors suggesting that these lower levels of donors get little professional benefit from their donations.

[Insert Table VIII here]

5. Robustness Analysis

My robustness checks mainly focus on three principle points of concern. The first point of concern is that my findings are a result of spurious correlation between political donations and accuracy. Second, one might be concerned that my findings are driven by an unobservable variable in the error term which is correlated with both donation propensity and accuracy. And third, there may be concerns that my results are a function of data snooping in the form of my choice of the big donor threshold. I have already attempted to address these concerns in the tests above, but these additional robustness checks may help to alleviate doubt.

First to address concerns over spurious correlation, I examine the regression of year t accuracy for big donors in year t+1 on various control variables including a binary variable for

year t+1 big donors. Essentially this is testing whether big donors are more accurate before they become big donors. The implications are similar to a test using analyst fixed effects, but with a more specifically formulated regression equation. In Table IX in Appendix 2, I show that analysts who will become big donors the following year, are no more accurate than other analysts in year t. Indeed, the sign on *future big donor* is negative (but insignificant), suggesting that if anything these analysts are slightly less accurate prior to becoming big donors. The contemporaneous big donors (*big donor*) continue to be more accurate. This implies that my results are not due to spurious correlations given that these analysts are not more accurate until the year when they first become major political donors.

[Insert Table IX here]

Second, to address concerns that my results may be driven by an unobservable variable bias residing in the error term, I perform three additional tests. In Table X, I regress accuracy on residual errors, error squared, error cubed, and the natural log of the error term. This has the effect of examining if there is any relationship between the model innovation term and accuracy. Any unobservable effects bias should be captured by these error term coefficients. In Table X, I use the error terms from the model from Table IV, column 3, but the results are similar when using other models from other tables. Table X shows that there is no significant relationship between any of the error term coefficients and accuracy. This suggests that most of the variation in the innovation of the regression is a result of random noise rather than a systematic unobservable variable which impacts accuracy.

[Insert Table X here]

In Table XI, I use a first differences procedure among analysts which should capture the effect of differences in unobservable variables between analysts. Here I regress the difference in

accuracy between each big donor and the mean accuracy of the other analysts on the difference in other variables between the two groups. This results in regressions with 44,259 observations and variables which are the difference between the value for the big donor analyst and a certain covered firm in a given quarter, and the mean value for that variable for all other analysts. The results in Table XI show that the difference in being a big donor and not being a big donor has a significant effect on accuracy, while most of the other variables have a negligible effect. Since using this first differences procedure has the effect of removing unobserved variables, yet the effects of being a big donor analyst remain consistent, this suggests that the observed effects of the *big donor* coefficient are not being driven by a hidden component in the error term.

[Insert Table XI here]

In Table XII, I again use a first differences procedure, but with a time trend interaction variable based on the year. In this case, I use the difference between each big donor analysts and all other analysts in a given year. This interaction term captures the effects of time-varying unobservable variation in the error term. As above, Table XII shows that being a big donor analyst is a consistent indicator of greater accuracy. This increased accuracy is present after removing unobservable factors that may vary with time as shown by the significance on the interaction of the time trend and the big donor coefficient. Table XII also serves to demonstrate that my results are not driven by a particular period in time, but instead appear to hold throughout most of my 20 year sample period, both before and after RegFD.

[Insert Table XII here]

Finally, to address concerns that my results are driven by a judicious choice of big donor thresholds, I perform a standard accuracy regression with a simple log of donation amount in dollars coefficient, a donation percentile coefficient, and a donation squared coefficient. As

Table XIII shows, neither the simple donation amounts, nor the percentiles of donations has a positive and statistically significant effect suggesting that any increased accuracy is isolated to a subset of the donor population. In contrast, donation amount squared does have a small statistically positive effect which reflects the fact that donors contributing large quantities are generally the ones driving my results. This is consistent with the findings of Table VIII.

[Insert Table XIII here]

6. Conclusion

In this paper, I show that political connections are one mechanism by which analysts can improve their earnings accuracy. These results hold in the post-Reg FD period, and are not driven by simple association between greater levels of political activity and higher levels of analyst accuracy. Instead, analysts are more accurate when they make substantial contributions to politicians. This result may be due to these analysts explicitly trading campaign contributions for information, or it may be due to the analyst simply having a social relationship with the politician. Accuracy is greater for analysts who make donations closer to their earnings estimate release date, have a geographic link to a politician, and when the firm covered by the analyst has an economic link to the government. These results hold after accounting for various control variables and fixed effects for analysts, years, covered firms, and brokerage firms. Further, the increased accuracy holds after comparing analysts making significant donations with other comparable peer analysts covering the same firms and making earnings estimates at the same point in time.

My results demonstrate one mechanism by which analysts continue to provide value to investors, and they provide a possible reason for the rapid rise in the political intelligence industry over the last decade. While most analysts do not have the political connections

necessary to gain useful information for clients, it is possible that other mechanisms for gaining useful information exist and that analysts engaging in unconventional research activities that may provide significant value to investors. I leave the investigation of alternative means of useful information gathering to future researchers.

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8. Appendices

Appendix 1: Tables

Table I: Univariate and Descriptive Statistics on Analyst Political Donations

Average campaign spending by winning House member in a 2 year campaign ending in 2012 was $1,439,997, while in the Senate (6 year campaign) it was $9,782,702. These figures have more risen by a factor of three since 1992.Single Contributions are one contribution by a single analyst. Analyst yearly contributions are annual contribution amount by a single analyst and are made up of one or more single contributions. Analyst yearly contributions to Republicans and Democrats are the contribution amounts directed by a single analyst to all members of one party or the other. Analyst total sample contributions are the sum of all contributions made by a single analyst throughout the entire 20 year sample period. Analyst total sample contributions to Republicans and Democrats are the sum of all contributions to each party for a single analyst during the entire sample period. Firm contributions are defined in the same fashion as analyst contributions but with contributions aggregated by brokerage or research firm rather than by individual analyst. Firm contributions displayed here include only the donations by analysts and do not include any donations by other types of firm employees such as mangers.

	Mean	Median	75%	90%	95%	99%	Max	Obs
Analyst Contributions	1,416.2	836.0	1,500.0	2,500.0	4,700.0	10,000.0	150,000.0	16,512
Analyst Contributions to Republican Candidates	1,452.3	1,000.0	1,500.0	2,500.0	4,600.0	15,000.0	56,249.0	10,078
Analyst Contributions to Democrat Candidates	1,452.5	750.0	1,250.0	2,500.0	4,600.0	15,350.0	68,800.0	9,755
Analyst Lifetime Contributions	14,096.3	3,200.0	9,800.0	31,768.0	60,274.0	215,200.0	519,299.0	1,789
Firm Yearly Contributions (By Analysts Alone)	18,777.8	2,500.0	9,925.0	37,828.0	78,150.0	252,175.0	1,484,455.0	2,559
Firm Yearly Contributions to Republican Candidates	8,614.5	2,000.0	5,900.0	20,700.0	36,000.0	129,660.0	490,424.0	1,697
Firm Yearly Contributions to Democrats Candidates	9,269.1	2,000.0	6,250.0	21,250.0	38,550.0	112,090.0	873,600.0	1,528
Firm Lifetime Contributions (By Analysts Alone)	356,901.7	56,314.0	189,654.0	802,891.0	1,672,733.0	4,371,660.0	11,700,000.0	2,559

Table II: Univariate Statistics on Analyst Estimate Accuracy and Recommendations

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *Actual EPS* is the actual earnings per share reported by a given firm in one quarter. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney.

Panel A

	Mean	Median	95th%	Standard Deviation	Observations
Price Scaled Accuracy (PSA)	0.07	0.04	2.42	9.63	445,812
Above Median Accuracy	0.50	0.00	1.00	0.50	445,812
Actual EPS	2.19	0.59	6.74	8.95	445,812
Days Before	49.35	36.00	88.00	37.40	445,812
Gov't Connection	0.25	0.00	1.00	0.43	445,812
ln MV	5.04	5.19	8.69	2.44	445,812
ln D2A	-0.79	-0.62	-0.05	0.81	445,812
ln MB	7.18	7.04	11.19	2.17	445,812
Cash-to-Debt	1.08	0.12	3.72	5.36	445,812
Donor	0.21	0.00	1.00	0.41	445,812
Big Donor	0.01	0.00	0.00	0.10	445,812
All Star	0.02	0.00	0.00	0.11	445,812
Bulge Bracket	0.16	0.00	1.00	0.36	445,812

Panel B - Big Donor Analysts

	Mean	Median	95th%	Standard Deviation	Observations
Price Scaled Accuracy	0.03	0.01	1.50	2.137	8,736
Above Median Accuracy	0.62	1.00	1.00	0.56	8,736
Actual EPS	2.15	0.60	7.14	9.20	8,736
Days Before	44.67	32.00	86.00	31.10	8,736
Days to Donation	85.46	119.00	328.00	127.71	8,736
Gov't Connection	0.36	0.00	1.00	0.48	8,736
Geographic Connection	0.64	1.00	1.00	0.73	8,736
Committee Connection	0.41	0.00	1.00	0.54	8,736
All Star	0.08	0.00	1.00	0.21	8,736
Bulge Bracket	0.22	0.00	1.00	0.41	8,736

Panel C - Partisan Firm Analysts

	Mean	Median	95th%	Standard Deviation	Observations
Price Scaled Accuracy	0.16	0.05	1.00	3.32	162,240
Above Median Accuracy	0.50	1.00	1.00	0.50	162,240
Actual EPS	2.30	0.63	6.36	5.92	162,240
Gov't Connection	0.28	0.00	1.00	0.43	162,240
Big Donor	0.05	0.00	1.00	0.16	162,240
Donor	0.48	0.00	1.00	0.50	162,240
All Star	0.02	0.00	0.00	0.10	162,240
Bulge Bracket	0.09	0.00	1.00	0.30	162,240

Table III: Correlation Coefficients

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *Actual EPS* is the actual earnings per share reported by a given firm in one quarter. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively.

	Donor	Partisan Firm	Scaled Accuracy	Above Median Accuracy	Days Before	Gov't Connection	ln MV	ln D2A	ln MB	Cash-to-Debt	All Star
Big Donor	0.196***	0.0451***	-0.034**	0.028***	-0.021	0.141***	-0.018	-0.003	0.087***	-0.015	0.027**
Donor	1.000	0.313***	0.016**	0.040***	0.010	0.172***	-0.017	0.004	0.112***	-0.044***	0.198***
Partisan Firm		1.000	-0.010*	0.017**	-0.042	0.058*	0.001	-0.006	0.009	0.099***	0.019*
PSA			1.000	-0.337***	0.154***	0.002	-0.046*	0.013*	0.100***	-0.033***	-0.280***
Above Median Accuracy				1.000	-0.229***	-0.003	0.087***	0.017**	0.137***	0.289***	0.351***
Days Before					1.000	-0.023**	-0.052***	-0.097***	0.215***	0.074***	-0.011*
Gov't Connection						1.000	0.071***	0.322***	-0.219***	-0.095***	-0.022**
ln MV							1.000	0.268***	-0.534***	-0.269***	-0.022**
ln D2A								1.000	-0.211***	-0.523***	-0.116***
ln MB									1.000	-0.534***	-0.358***
Cash-to-Debt										1.000	0.120***

Table IV, Panel A: The Impact of Political Donations on Price Scaled Accuracy with Firm FEs

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. (Number Range) *Days to Donation* is a binary variable equal to 1 if the difference between a big donor analyst's most recent donation and most recent earnings announcement date is equal to that range or less. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Analyst Tenure* is the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. Analyst tenure for analysts without LinkedIn profiles are simply recorded as the number of quarters they appear in the sample. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Opposition_Congress_Analyst* is a binary variable equal to one if the analyst only makes donations to the party not in control of the House of Representatives in a given year. *Democratic Congress* is a binary variable equal to 1 if the Democratic party is in control of Congress. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

Table IV, Panel A Contd.:

	PSA	Above Median Accuracy	PSA	Above Median Accuracy	PSA	Above Median Accuracy
	(1)	(2)	(3)	(4)	(5)	(6)
Donor	0.007	-0.008	0.012*	-0.022*	0.003	-0.005
	(0.115)	(0.131)	(0.096)	(0.081)	(0.177)	(0.120)
Big Donor	-0.023***	0.091***	-0.027**	0.093**	-0.014**	0.025**
	(0.000)	(0.000)	(0.043)	(0.022)	(0.048)	(0.039)
0 - 60 Days to Donation			-0.019**	0.044***	-0.012**	0.015**
			(0.015)	(0.007)	(0.046)	(0.034)
60-180 Days to Donation			-0.008**	0.017**	-0.005*	0.010*
			(0.030)	(0.019)	(0.098)	(0.082)
180-360 Days to Donation			-0.006*	0.009*	0.002	0.004
			(0.079)	(0.060)	(0.148)	(0.161)
Days Before (10s)	0.022***	-0.007***	0.021***	-0.005***	0.024***	-0.011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All Star	-0.024**	0.016*	-0.018*	0.014*	-0.039***	0.008***
	(0.036)	(0.077)	(0.055)	(0.069)	(0.000)	(0.000)
Bulge Bracket	-0.006	0.004	-0.008	0.007	-0.017*	0.012*
	(0.128)	(0.163)	(0.123)	(0.159)	(0.089)	(0.069)
ln MV	-0.066***	0.032***	-0.067***	0.029***	-0.032***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Debt to Assets	0.067***	-0.010***	0.066***	-0.012***	0.026***	-0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln Market-to-Book	-0.110***	0.034***	-0.109***	0.032***	-0.041***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash to Debt	0.002	-0.015***	0.001	-0.017***	-0.001	-0.027*
	(0.192)	(0.000)	(0.252)	(0.000)	(0.368)	(0.045)
Analyst Tenure	-0.008*	0.011*	-0.007	0.010	-0.005	0.006
	(0.097)	(0.084)	(0.126)	(0.103)	(0.234)	(0.198)
Gov't Connection			0.003	0.012	0.023	0.011
			(0.512)	(0.386)	(0.132)	(0.261)
Gov't Connection*Big Donor			-0.028***	0.045***	-0.019**	0.056***
			(0.000)	(0.000)	(0.023)	(0.000)
Opposition_Congress_ Analyst			0.011*	-0.059**	0.008*	-0.024*
			(0.055)	(0.036)	(0.075)	(0.060)
Partisan Firm			-0.011	0.023*	-0.013	0.012
			(0.117)	(0.078)	(0.154)	(0.185)
Democratic Congress					0.021	0.006
					(0.315)	(0.262)
Year Dummies	Yes	Yes	Yes	Yes		
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
NASDAQ Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Covered Firm FE					Yes	Yes
Observations	445,812	445,812	445,812	445,812	445,812	445,812
R Squared	0.062	0.074	0.101	0.119	0.412	0.448

Table IV, Panel B: Price Scaled Accuracy with Firm, Brokerage, Year, and Quarter FEs

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. *Days to Donation* equals the difference between a big donor analyst's most recent donation and most recent earnings announcement date. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Analyst Tenure* is the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. Analyst tenure for analysts without LinkedIn profiles are simply recorded as the number of quarters they appear in the sample. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Opposition_Congress_Analyst* is a binary variable equal to one if the analyst only makes donations to the party not in control of the House of Representatives in a given year. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

	PSA	Above Median Accuracy
	(1)	(2)
Days to Donation (10s)	-0.0009***	-0.0004***
	(0.002)	(0.000)
Big Donor	-0.019*	0.014**
	(0.057)	(0.033)
Days Before (10s)	0.020***	-0.011***
	(0.000)	(0.000)
All Star	-0.022*	0.005**
	(0.070)	(0.041)
Analyst Tenure	-0.003	0.006
	(0.157)	(0.149)
Gov't Connection*Big Donor	-0.007	0.032*
	(0.110)	(0.086)
Opposition_Congress_ Analyst	0.003	-0.015
	(0.191)	(0.153)
Year Dummies	Yes	Yes
Quarter Dummies	Yes	Yes
NASDAQ Dummy	Yes	Yes
Brokerage Firm FEs	Yes	Yes
Target Firm FE	Yes	Yes
Observations	29,512	29,512
R Squared	0.563	0.641

Table V: The Impact of Political Donations on Price Scaled Accuracy with Analyst FEs

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. (Number Range) *Days to Donation* is a binary variable equal to 1 if the difference between a big donor analyst's most recent donation and most recent earnings announcement date is equal to that range or less. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Opposition_Congress_Analyst* is a binary variable equal to one if the analyst only makes donations to the party not in control of the House of Representatives in a given year. *Democratic Congress* is a binary variable equal to 1 if the Democratic party is in control of Congress. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

Table V Contd.:

	PSA	Above Median Accuracy
	(1)	(2)
Donor	0.012	-0.004
	(0.376)	(0.352)
0 - 60 Days to Donation	-0.051*	0.036*
	(0.082)	(0.070)
60-180 Days to Donation	-0.030	0.021*
	(0.115)	(0.097)
180-360 Days to Donation	-0.024	0.010
	(0.161)	(0.134)
Big Donor	-0.238*	0.272*
	(0.095)	(0.088)
Days Before (10s)	0.025***	-0.013
	(0.000)	(0.000)
All Star	-0.010	0.019
	(0.186)	(0.159)
Bulge Bracket	-0.005	0.007
	(0.241)	(0.189)
ln MV	-0.075***	0.035***
	(0.000)	(0.000)
ln Debt to Assets	0.070***	-0.026***
	(0.000)	(0.000)
ln Market-to-Book	-0.104***	0.037***
	(0.000)	(0.000)
Cash to Debt	0.005**	-0.018***
	(0.010)	(0.000)
Gov't Connection	-0.014	0.010
	(0.784)	(0.1527)
Gov't Connection*Big Donor	-0.044**	0.038***
	(0.021)	(0.009)
Opposition_Congress_Analyst	0.088***	-0.029*
	(0.008)	(0.053)
Partisan Firm	-0.011	0.002
	(0.177)	(0.148)
Democratic Congress	0.008	-0.006
	(0.701)	(0.421)
Quarter Dummies	Yes	Yes
NASDAQ Dummy	Yes	Yes
Analyst FEs	Yes	Yes
Observations	445,812	445,812
R Squared	0.291	0.348

Table VI: The Impact of Political Donations on Price Scaled Accuracy Controlling for Industry and Geographic Location

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. (Number Range) *Days to Donation* is a binary variable equal to 1 if the difference between a big donor analyst's most recent donation and most recent earnings announcement date is equal to that range or less. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Analyst Tenure* is the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. Analyst tenure for analysts without LinkedIn profiles are simply recorded as the number of quarters they appear in the sample. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Geographic Link* is a binary variable equal to one if a big donor analyst works in the same state as the politician to whom the analyst donates the most money in a given year. *Committee Link* is a binary variable equal to 1 if the analyst donates money to a politician serving on a committee that oversees the regulation of the industry of a firm covered by the analyst. *Democratic Congress* is a binary variable equal to 1 if the Democratic party is in control of Congress. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

Table VI Contd.:

	PSA	Above Median Accuracy	PSA	Above Median Accuracy
	(1)	(2)	(3)	(4)
Donor	0.023*	-0.017	0.009	-0.016
	(0.090)	(0.180)	(0.125)	(0.116)
Big Donor	-0.018*	0.052**	-0.037*	-0.029**
	(0.077)	(0.048)	(0.062)	(0.034)
0 - 60 Days to Donation	-0.078**	0.036**	-0.081**	0.038**
	(0.021)	(0.010)	(0.019)	(0.011)
60-180 Days to Donation	-0.059	0.034*	-0.060	0.036*
	(0.145)	(0.082)	(0.144)	(0.081)
180-360 Days to Donation	-0.013	0.006	-0.015	0.005
	(0.182)	(0.159)	(0.181)	(0.160)
All Star	-0.018***	0.023***	-0.013**	0.017**
	(0.000)	(0.000)	(0.022)	(0.039)
Bulge Bracket	-0.005	0.007	-0.003	0.004
	(0.183)	(0.211)	(0.274)	(0.304)
ln MV	-0.064***	0.031***	-0.064***	0.031***
	(0.000)	(0.000)	(0.000)	(0.000)
ln Debt to Assets	0.069***	-0.026***	0.069***	-0.025***
	(0.000)	(0.000)	(0.000)	(0.000)
ln Market-to-Book	-0.091***	0.033***	-0.091***	0.033***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash to Debt	0.003*	-0.004***	0.001	-0.005***
	(0.0674)	(0.000)	(0.119)	(0.000)
Gov’t Connection			0.006	-0.009
			(0.693)	(0.614)
Gov’t Connection*Big Donor			-0.063**	0.049**
			(0.020)	(0.018)
Geographic Link			-0.064**	0.030**
			(0.041)	(0.012)
Committee Link	0.024*	0.039***		
	(0.063)	(0.000)		
Partisan Firm	0.016	-0.039*	0.077	-0.048**
	(0.215)	(0.068)	(0.161)	(0.047)
Democratic Congress	0.011	-0.007	0.004	-0.004
	(0.137)	(0.242)	(0.190)	(0.289)
Year Dummies	Yes	Yes	Yes	Yes
State Dummies			Yes	Yes
NASDAQ Dummy	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes		
Observations	445,812	445,812	445,812	445,812
R Squared	0.155	0.265	0.172	0.250

Table VII: Difference in Differences around Analysts Becoming Big Donors

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses. The regression shows difference in analyst accuracy for two different analysts covering the same firm across quarters before and after one of the analysts makes large donations and becomes a big donor. Most of the control variables including fixed effects drop out under this specification.

Difference in Variables	PSA	Above Median Accuracy
	(1)	(2)
Big Donor	-0.005*	0.009*
	(0.091)	(0.063)
All Star	-0.012*	0.018*
	(0.054)	(0.041)
Bulge Bracket	-0.001	0.002
	(0.635)	(0.576)
Gov't Connection*Big Donor	-0.011**	0.019**
	(0.035)	(0.026)
Observation Pairs	8,736	8,736
R Squared	0.051	0.079

Table VIII: Accuracy Based on Quartiles of Donations

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. (Number Range) *Days to Donation* is a binary variable equal to 1 if the difference between a big donor analyst's most recent donation and most recent earnings announcement date is equal to that range or less. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Analyst Tenure* is the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. Analyst tenure for analysts without LinkedIn profiles are simply recorded as the number of quarters they appear in the sample. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Opposition_Congress_Analyst* is a binary variable equal to one if the analyst only makes donations to the party not in control of the House of Representatives in a given year. *Democratic Congress* is a binary variable equal to 1 if the Democratic party is in control of Congress. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

	PSA	Above Median Accuracy	PSA	Above Median Accuracy
	(1)	(2)	(3)	(4)
Donor Quartile 1	-0.023*	0.034*		
	(0.098)	(0.095)		
Donor Quartile 2	-0.005	0.008		
	(0.417)	(0.304)		
Donor Quartile 3	0.009	-0.034		
	(0.131)	(0.117)		
Donation Amount			0.002	-0.001
			(0.485)	(0.512)
Days Before (10s)	0.031***	-0.022***	0.032***	-0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
All Star	-0.019*	0.005**	-0.019*	0.004**
	(0.076)	(0.040)	(0.078)	(0.041)
Analyst Tenure	-0.004	0.005	-0.003	0.007
	(0.148)	(0.143)	(0.151)	(0.149)
Gov't Connection*Quartile1	-0.005	0.017*	-0.008*	0.023*
	(0.124)	(0.099)	(0.091)	(0.077)
Year Dummies	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes
NASDAQ Dummy	Yes	Yes	Yes	Yes
Brokerage Firm FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	445,812	445,812	445,812	445,812
R Squared	0.192	0.168	0.193	0.171

Appendix 2: Additional Tests

Table IX: Accuracy of Future Big Donors

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. *Future Big Donor* is a binary variable equal to 1 if next year the analyst donates enough money to one or more candidates to fall into the top 5% of all donors nationally. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Analyst Tenure* is the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. Analyst tenure for analysts without LinkedIn profiles are simply recorded as the number of quarters they appear in the sample. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Opposition_Congress_Analyst* is a binary variable equal to one if the analyst only makes donations to the party not in control of the House of Representatives in a given year. *Democratic Congress* is a binary variable equal to 1 if the Democratic party is in control of Congress. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

Table IX Contd.:

	PSA	Above Median Accuracy	PSA	Above Median Accuracy
	(1)	(2)	(3)	(4)
Donor	0.008	-0.010	0.005	-0.007
	(0.107)	(0.128)	(0.151)	(0.142)
Big Donor	-0.019**	0.057***	-0.013**	0.028**
	(0.011)	(0.000)	(0.042)	(0.045)
Future Big Donor	0.004	0.002	0.001	-0.003
	(0.351)	(0.437)	(0.516)	(0.398)
Days Before (10s)	0.020***	-0.009***	0.021***	-0.013***
	(0.000)	(0.000)	(0.000)	(0.000)
All Star	-0.026**	0.015*	-0.031***	0.010***
	(0.042)	(0.079)	(0.020)	(0.016)
Bulge Bracket	-0.005	0.004	-0.018*	0.012*
	(0.129)	(0.163)	(0.090)	(0.070)
ln MV	-0.065***	0.034***	-0.033***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
ln Debt to Assets	0.065***	-0.011***	0.026***	-0.014***
	(0.000)	(0.000)	(0.000)	(0.000)
ln Market-to-Book	-0.111***	0.034***	-0.042***	0.024***
	(0.000)	(0.000)	(0.000)	(0.000)
Cash to Debt	0.003	-0.016***	-0.001	-0.026*
	(0.189)	(0.000)	(0.370)	(0.046)
Analyst Tenure	-0.009*	0.010*	-0.005	0.006
	(0.098)	(0.086)	(0.233)	(0.200)
Gov't Connection			0.024	0.011
			(0.130)	(0.260)
Gov't Connection*Big Donor			-0.019**	0.055***
			(0.024)	(0.000)
Opposition_Congress_ Analyst			0.007*	-0.022*
			(0.077)	(0.061)
Partisan Firm			-0.012	0.011
			(0.155)	(0.186)
Democratic Congress			0.020	0.006
			(0.313)	(0.263)
Year Dummies	Yes	Yes		
Quarter Dummies	Yes	Yes	Yes	Yes
NASDAQ Dummy	Yes	Yes	Yes	Yes
Covered Firm FE	Yes	Yes	Yes	Yes
Observations	445,812	445,812	445,812	445,812
R Squared	0.062	0.075	0.413	0.448

Table X: The Relationship between Accuracy and Unobservable Factors

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Error Term* is the residuals for each analyst after using the basic model specified in Table IV, column 3 and 4. *Error Term Squared* is the square of the residuals for each analyst after using the basic model specified in Table IV, column 3 and 4. *Error Term Cubed* is the cube of the residuals for each analyst after using the basic model specified in Table IV, column 3 and 4. *Log of the Error Term* is the natural log of the residuals for each analyst after using the basic model specified in Table IV, column 3 and 4.

Difference in Variables	PSA	Above Median Accuracy	PSA	Above Median Accuracy
	(1)	(2)	(3)	(4)
Error Term			0.025 (0.658)	-0.018 (0.571)
Error Term Squared			0.8*E-06 (0.854)	-0.2*E-05 (0.741)
Error Term Cubed			-0.4*E-9 (0.974)	0.9*E-9 (0.931)
Log of the Error Term	0.115 (0.235)	-0.158 (0.176)		
Observation Pairs	445,812	445,812	445,812	445,812
R Squared	0.000	0.001	0.003	0.008

Table XI: Accuracy of Big Donors Using First Differences

Diff PSA is difference between each Big Donor's PSA and the mean of all other analysts. *Diff Above Median Accuracy* is the difference between big donor analysts and mean other analyst for a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. *Donor Diff* is the difference between big donor analysts and mean other analyst for a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor Diff* is a binary variable equal to 1 if the analyst in question is a big donor in the given year. *Days Before Diff* is the difference between big donor analysts and mean other analyst for the number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star Diff* is the difference between big donor analysts and mean other analyst for a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket Diff* is the difference between big donor analysts and mean other analyst for a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV Diff* is the difference between big donor analysts and mean other analyst for the natural log of covered firm market capitalization. *Ln D2A Diff* is the difference between big donor analysts and mean other analyst for the natural log of the covered firm's debt to assets ratio. *Ln MB Diff* is the difference between big donor analysts and mean other analyst for the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt Diff* is the difference between big donor analysts and mean other analyst for the ratio of cash holdings of the covered firm to its liabilities. *Analyst Tenure Diff* is the difference between big donor analysts and mean other analyst for the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

	Diff PSA	Diff Above Median Accuracy
	(1)	(2)
Donor Diff	0.033	-0.027
	(0.268)	(0.319)
Big Donor Diff	-0.011*	0.024**
	(0.052)	(0.030)
Days Before Diff (10s)	0.148	-0.079
	(0.193)	(0.212)
All Star Diff	-0.160	0.304
	(0.335)	(0.247)
Bulge Bracket Diff	-0.056	0.062
	(0.405)	(0.349)
ln MV Diff	-0.116	0.086
	(0.197)	(0.262)
ln Debt to Assets Diff	0.136	-0.059
	(0.152)	(0.175)
ln Market-to-Book Diff	-0.100*	0.124*
	(0.090)	(0.081)
Cash to Debt Diff	0.087	-0.041
	(0.621)	(0.373)
Analyst Tenure Diff	-0.025	0.039
	(0.419)	(0.392)
Observations	44,259	44,259
R Squared	0.172	0.251

Table XII: Accuracy of Future Big Donors Using Time Varying First Differences

Diff Price Scaled Accuracy (PSA) is the difference in the absolute value of ((Estimate-Actual)/Share Price)*100 between the big donor in question, and all other non-big donor analysts in a given year. *Diff Above Median Accuracy* is difference in a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period and the mean of the same indicator for all other non-big donor analysts in a given year. *Year Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. *Other Controls* include differences for each variable between the analyst and the mean of all other non-big donor analysts in a given year. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

Table XII Contd.:

	Diff PSA	Diff Above Median Accuracy
	(1)	(2)
1992Big Donor	-0.009*	0.018**
	(0.063)	(0.020)
1993Big Donor	-0.003	0.005
	(0.164)	(0.151)
1994Big Donor	-0.006*	0.008*
	(0.089)	(0.084)
1995Big Donor	-0.007*	0.011*
	(0.085)	(0.061)
1996Big Donor	-0.009*	0.014*
	(0.065)	(0.056)
1997Big Donor	-0.007*	0.012*
	(0.084)	(0.059)
1998Big Donor	-0.014**	0.016**
	(0.045)	(0.038)
1999Big Donor	-0.002	0.003
	(0.247)	(0.185)
2000Big Donor	-0.002	0.004
	(0.218)	(0.177)
2001Big Donor	-0.001	0.004
	(0.287)	(0.193)
2002Big Donor	-0.004	0.007
	(0.199)	(0.120)
2003Big Donor	-0.006	0.009*
	(0.113)	(0.088)
2004Big Donor	-0.013**	0.015**
	(0.038)	(0.024)
2005Big Donor	-0.012*	0.013*
	(0.052)	(0.049)
2006Big Donor	-0.017**	0.023**
	(0.031)	(0.026)
2007Big Donor	-0.016**	0.020**
	(0.033)	(0.031)
2008Big Donor	-0.018**	0.025**
	(0.024)	(0.023)
2009Big Donor	-0.024**	0.032**
	(0.019)	(0.015)
2010Big Donor	-0.027**	0.034**
	(0.013)	(0.012)
2011Big Donor	-0.020**	0.028**
	(0.022)	(0.027)
2012Big Donor	-0.023**	0.030**
	(0.019)	(0.017)
Other Controls	YES	YES
Observations	44,259	44,259
R Squared	0.462	0.610

Table XIII: Accuracy Based on Dollar Donation Amounts

Price Scaled Accuracy (PSA) is absolute value of ((Estimate-Actual)/Share Price)*100, meaning that negative coefficients indicate greater accuracy. *Above Median Accuracy* is a binary variable equal to one if the analyst's forecast was above the median level of accuracy for the given period. Thus positive coefficients indicate greater accuracy here. *Donor* is a binary variable equal to 1 if the analyst donates money to a federal candidate for an election during the sample period 1992-2012. *Big Donor* is a binary variable equal to 1 if the analyst donates enough money in a given year to one or more candidates to fall into the top 5% of all donors nationally. (Number Range) *Days to Donation* is a binary variable equal to 1 if the difference between a big donor analyst's most recent donation and most recent earnings announcement date is equal to that range or less. *Days Before* is the difference in number of days between an analyst's earnings estimate and the actual earnings announcement of the firm. *All Star* is a binary variable equal to 1 if the analyst is labeled an All Star analyst in a given year by Institutional Investor magazine. *Bulge Bracket* is a binary variable equal to 1 if the analyst works for one of the following firms in a given year: JP Morgan, Citigroup, Morgan Stanley, Dean Witter, Goldman Sachs, Lehman Brothers, Bear Sterns, Salomon Brothers, or Smith Barney. *Ln MV* is the natural log of covered firm market capitalization. *Ln D2A* is the natural log of the covered firm's debt to assets ratio. *Ln MB* is the natural log of the covered firm's market to book value where book value is the tangible book equity of the firm (tangible assets – liabilities). *Cash-to-Debt* is the ratio of cash holdings of the covered firm to its liabilities. *Analyst Tenure* is the larger of number of quarters an analyst appears in the sample, and 4 times the number of years (4 quarters in a year) the analyst's LinkedIn profile lists them as working as analyst. Analyst tenure for analysts without LinkedIn profiles are simply recorded as the number of quarters they appear in the sample. *Gov't Connection* is a binary variable equal to one if the firm being covered by the analyst receives more than 10% of sales from the government, or is in a heavily regulated industry. *Opposition_Congress_Analyst* is a binary variable equal to one if the analyst only makes donations to the party not in control of the House of Representatives in a given year. *Democratic Congress* is a binary variable equal to 1 if the Democratic party is in control of Congress. *Partisan Firm* is a binary variable equal to one if the analyst works for a firm where more than 66% of all donations in a given year go to one party. *, **, and *** indicate 10%, 5%, and 1% significance respectively. P-scores are reported in parentheses.

	PSA	Above Median Accuracy	PSA	Above Median Accuracy	PSA	Above Median Accuracy
	(1)	(2)	(3)	(4)	(5)	(6)
Log of Donation Amount	-0.011 (0.137)	0.004 (0.223)				
Donation Amount Squared			-0.1*E-10 (0.159)	0.1*E-5 (0.355)		
Donation Percentile					-0.001 (0.435)	0.001 (0.516)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
NASDAQ Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Brokerage Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	445,812	445,812	445,812	445,812	445,812	445,812
R Squared	0.526	0.914	0.505	0.907	0.512	0.910