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Consistency between earnings forecasts and stock recommendations : the effect of political connections

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CONSISTENCY BETWEEN EARNINGS FORECASTS AND STOCK RECOMMENDATIONS: THE EFFECT OF POLITICAL CONNECTIONS

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DEDICATION

I dedicate this dissertation to my wife, Pilar Alfonso. Without her love and support, this achievement would never have been possible. She has always been by my side and believed in me without hesitation. She has provided me with words of wisdom and encouragement every day over the past four years. She has always kept a positive attitude and a remarkably strong character founded on deep faith. She is truly an amazing person with angelic strength. She is the kind of woman that makes everything look so easy yet I marvel at how much dedication, hard work, and devotion she puts into being a respectable wife and a sweet and caring mother. It was because she believed in me that I had the courage to believe in myself. I can think of no better words to explain my appreciation for her love and support than these: *"I love you, not only for what you are, but for what I am when I am with you."* (Roy Croft)

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ABSTRACT

Financial analysts' earnings forecasts are more consistent with stock recommendations when their earnings forecasts are more accurate (Loh and Mian 2006, Ertimur et al. 2007). This suggests that analysts use other information in their private valuation models in addition to earnings forecasts especially when earnings have greater uncertainty. Recent studies show that political connections are important for firm valuation and are associated with future positive returns and future positive operating performance (Faccio 2006, Cooper et al. 2010). In this study, I examine how a firm's political connections affect stock recommendation informativeness as well as the efficiency with which analysts translate their earnings forecasts into stock recommendations. Using data from the Federal Election Commission through the Center for Responsive Politics from 1993 – 2011, I first show that analysts' recommendations are less informative when firms have political connections. This relation holds for both All-Star and non-All-Star analysts, upgrade and downgrade recommendations, as well as initiation and non-initiation recommendations. Second. I show that analysts' earnings forecast accuracy is less consistent with recommendation informativeness when firms are politically connected. This inconsistency appears to be driven by non-All-Star analysts, upgrade recommendations, and non-initiation recommendations. The findings of this study imply that political connection information is one source of important nonfinancial disclosure that influences how analysts map their earnings forecasts into stock recommendations.

1. INTRODUCTION

Studies show that financial analysts' earnings forecasts and stock recommendations are more consistent when their earnings forecasts are more accurate (Loh and Mian 2006, Ertimur et al. 2007). This implies that analysts consider factors other than earnings forecasts in valuing a firm especially when earnings have greater uncertainty. If earnings are less predictable or of lower quality, analysts will use more idiosyncratic information as inputs into private valuation models which in turn guide the stock recommendation. This suggests that when a factor is consistent with more (less) certain information being provided through the recommendation, there will be a positive (negative) relation between such a factor and recommendation informativeness[1]. It follows that the association between recommendation informativeness and forecast accuracy also depends on the certainty of the analysts' earnings forecasts.

One important area where the certainty of earnings forecasts can be affected is the existence of political connections. Recent work in the finance and economics literature documents that political connections are value relevant and affect a firm's future operating performance (Faccio 2006, Goldman et al. 2009, Cooper et al. 2010). In addition, Chen et al. (2010) find that financial analysts have worse forecast accuracy for politically connected firms. These findings suggest that political connections affect *both* analysts' earnings forecasts and stock recommendations. Therefore, in this study, I first examine whether political connections affect analysts' stock recommendation informativeness. Second, I investigate whether political connections affect the efficiency with which analysts translate their earnings forecasts into stock recommendations. In essence, I seek to determine whether analysts' earnings forecast accuracy is

[1] In this study I use the term " recommendation informativeness" instead of "recommendation profitability" to emphasize that the main objective of this study is to test the overall information content of stock recommendations for politically connected firms rather than exploiting a trading strategy aimed at generating abnormal returns.

more or less consistent with stock recommendation informativeness when the firms they follow have political connections.

Traditionally, the financial analyst literature has focused on either analysts' earnings forecast accuracy or stock recommendation informativeness independently from one another. Schipper (1991) states that the process of forecasting earnings is one of many pieces of information used to arrive at a stock recommendation. She argues that earnings forecasts are an important input into the analysts' final output (the stock recommendation) but are not the ultimate end product. Since Schipper (1991), studies have begun to examine how analysts actually use their earnings forecasts as inputs into generating stock recommendations. Loh and Mian (2006) show that analysts who are more accurate have more informative recommendations. Ertimur et al. (2007) show that this positive relation holds only when earnings are value relevant. In essence, earnings forecasts are less likely to be an essential input into the analysts' valuation model if the earnings are not an important determinant of firm value. This signifies that greater forecast accuracy is not always related to more informative recommendations. I contribute to this line of literature by examining how political connections alter the mapping of analysts' earnings forecasts into stock recommendations.

Since information on political connectedness matters to the market for firm valuation (Faccio 2006), it follows that analysts will incorporate this information into their private estimates of a firm's intrinsic value. Anecdotal evidence shows that analysts' reports often analyze the value of a firm's political connections as well as how this value contributes to the analysts' stock recommendation. For example, analyst Jonathan Litt writes, "The Catellus management team, and Mr. Rising in particular, have strong political connections and public policy expertise. We believe this is an important attribute of the company, as land development projects often have community and city political hurdles to overcome."[2] Analysts typically examine two facets of political connections: (1) whether the firm makes political contributions and to whom the contributions are made, and (2) whether officers, large shareholders, or members of the board of directors hold a top political position. Analysts are generally optimistic in their reports about firms' political connections, but they are also aware of the potential for increased risk. For example, Kevin St. Pierre writes, "Vernon Hill announced in 2003 that Commerce Bank would close down its political action committee amidst allegations that their significant political contributions were influencing government business in banking, bond underwriting, and insurance." Therefore, it is clear from analyst reports that political connection information affects both their earnings forecasts and stock recommendations. This study takes a more detailed look at how this information on political connectedness actually affects analysts' two primary research outputs.

In this study, I use data on political contributions[3] from the Federal Election Commission (FEC) through the Center for Responsive Politics. This database contains detailed information on the political candidates to whom firms contribute as well as the amounts contributed. Following Cooper et al. (2010), I design four proxies for political connectedness based on the following: (1) the number of supported candidates, (2) the number of supported, incumbent candidates

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[2] Other examples from *INVESTEXT* analysts' reports include: (1) "Freddie Mac's Richard Syron has held executive positions at the Federal Home Loan Bank, the Federal Reserve, and the American Stock Exchange. In addition to his doctorate in economics, he is known to be politically adept - something the board was searching for." – Jim Callahan; (2) "Among ICx Technologies' board of directors are former Energy Secretary Spencer Abraham and former Transportation Secretary Rodney Slater. The chairman of the board, Mark Mills, has done consulting to the White House and has worked with some of the federal research laboratories. These high-level connections may assist ICx in winning lucrative government contracts." - Michael Pierson; (3) "The Shaw Group's experience in restoration work along with its political contacts -CEO Bernhard was chairman of the Louisiana Democratic Party, and a former governor of Louisiana sits on Shaw's board - should help the company continue to win work associated with the Gulf Coast's restoration efforts." - John Kearney; (4) "Citigroup's upper management and directors, including Sandy Weill, Robert Willumstad, Charles Prince, and Robert Rubin, are well respected. Credibility and political connections will be as important as Citigroup's core fundamentals in the months ahead." - Craig Woker.

[3] I use the terms political connections, political contributions, campaign contributions, and political donations interchangeably throughout this study.

weighted by the length of the firm-candidate relationship, (3) the number of supported, incumbent candidates that hold office in the same state where the firm is headquartered, and (4) the number of supported, incumbent candidates weighted the power of the candidate.

I first examine how a firm's political connections affect analysts' stock recommendation informativeness. Political contributions are often characterized as long-term relationships between the firm and the political candidate in the form of implicit long-term contracts (Snyder 1992). Many political candidates reward firms with political favors assuming they win office and the opportunity to provide a favor arises. Therefore, because there are many elements of unpredictability regarding if the politician will be able to help the firm as well as when the potential favor will come to fruition, there is likely to be increased future earnings uncertainty. Even if analysts are not able to predict the short-term effects of political connections through earnings forecasts, the long-term horizon of stock recommendations should capture the impact of the change in expected future cash flows. Therefore, if analysts are able to incorporate the favorable (or unfavorable) effects of political connections into their stock recommendations, analysts' recommendations will be more informative for politically connected firms. Alternatively, if analysts are unable to use other information to resolve uncertainty effectively, analysts' recommendations will be less informative.

Second, I examine how political connections affect the relation between forecast accuracy and recommendation informativeness to shed light on how analysts actually use political information. Financial analysts have greater difficulty predicting the earnings of firms that have political connections (Chen et al. 2010). This is consistent with political favors disrupting the future earnings stream process in an unpredictable manner. Therefore, it is likely that due to the inherent uncertainty, analysts' recommendations will rely less on earnings forecasts in their private valuation models. Accordingly, there will be less association between recommendation informativeness and earnings forecast accuracy. On the other hand, it is possible that analysts with more experience covering politically connected firms or analysts who perform more private information search for these firms will have higher earnings forecast accuracy. Therefore, these analysts will rely more on earnings forecasts in their private valuation models. In this latter situation, there will be a greater association between recommendation informativeness and earnings forecast accuracy.

I find that analysts' stock recommendations are significantly less informative when the firms they follow are politically connected. I find that this negative relation holds for both All-Star and non-All-Star analysts, upgrade and downgrade recommendations, as well as initiation and non-initiation recommendations. I also show that analysts' earnings forecast accuracy is less consistent with stock recommendation informativeness for firms that have political connections. However, the negative relation between earnings forecast accuracy and recommendation informativeness for politically connected firms appears to be driven by non-All-Star analysts, upgrade recommendations, and non-initiation recommendations.

This study contributes to two separate strands of the analyst forecast literature and also to the political connections literature. First, I inform the literature that examines how analysts map their earnings forecasts into stock recommendations by documenting another important factor that influences this process. The evidence suggests that analysts rely less on earnings forecasts in private valuation models used to generate stock recommendations when firms have political connections. Second, I also contribute to the recent literature that examines how analysts use information on nonfinancial disclosures in their earnings forecasts. There is only one published study of which I am aware that examines how analysts' use of nonfinancial information influences forecast error. Specifically, Dhaliwal et al. (2012) find that analysts have greater forecast accuracy for firms that issue stand-alone corporate social responsibility reports. I contribute to this line of literature by documenting another important source of nonfinancial information, namely corporate political activity, which affects both analysts' earnings forecasts and stock recommendations. Third, I contribute to the political connections literature by showing that financial analysts are one channel through which information on political connections affects firm valuation. Many studies find that political connectedness is associated with an increase in firm value (Faccio 2006, Faccio and Parley 2009, Cooper et al. 2010). I show that part of this market reaction can be directly attributed to investors' interpretation of analysts' earnings forecasts and stock recommendations for firms that have political connections.

Section 2 and Section 3 provide a review of the relevant literature and hypothesis development. Section 4 and Section 5 consist of the measurement of political connections and research design. Section 6, Section 7, and Section 8 present the sample selection, results, and sensitivity analyses. Section 9 concludes the study.

2. BACKGROUND AND LITERATURE REVIEW

2.1. Mapping of Earnings Forecasts into Recommendations

Schipper (1991) motivated researchers to study analysts' decision-making process in more detail by examining how analysts' earnings forecasts are used as inputs into analysts' valuation models from which they calculate the intrinsic value of the firm and ultimately issue a stock recommendation. Prior literature then began to assess the effectiveness of analysts in transforming their earnings forecasts into stock recommendations. Loh and Mian (2006) show that analysts who are more accurate tend to have more profitable recommendations. Ertimur et al. (2007) extend this line of literature by showing that the positive relation between accuracy and profitability holds only for firms whose earnings are value relevant. They also show that analysts are more effective in translating their earnings forecasts into recommendations when they do not have conflicts of interests stemming from investment banking activities.

Another line of literature examines the relation between earnings forecasts and stock recommendations by using different valuation models as proxies for analysts' private valuation models. Bradshaw (2004) finds that there is a positive (negative) relation between stock recommendations and simple heuristic valuation models (residual income valuation models). This implies that analysts do not use their earnings forecasts in a sophisticated manner in generating recommendations. Simon and Curtis (2011) extend Bradshaw's work by showing that the negative relation between recommendations and residual income valuations is weakest for the most accurate analysts. Barniv et al. (2009) and Chen and Chen (2009) show that even though the relation between recommendations and sophisticated earnings models is negative, analysts are showing improvements in their translations of earnings forecasts into recommendations in the post regulations period. Ke and Yu (2009) analyze different explanations for why analysts do not effectively translate their earnings forecasts into recommendations. They argue that analysts could simply be unable to make this transformation in an efficient manner, could optimistically bias recommendations in order to obtain information from management, or could be affected by psychological biases. I extend this line of literature by examining a different factor pertinent to firm valuation, namely political connections, which affects how analysts translate earnings forecasts into stock recommendations.

2.2. Political Contributions

In this study, I use political contributions to proxy for a firm's political connections.[4] There are two competing theories in the economics and political science literature that seek to explain why firms make political contributions to politicians: the theory of investment in political capital and the theory of consumption.

If political contributions are an investment in political capital, the firm will realize returns on its investment as the politician grants favors to the firm throughout his tenure in office. Stigler (1971) theorizes that government officials influence firms' financial performance through direct subsidies, favorable tax treatment, government contracts, and barriers to entry. However, politicians who receive contributions can also affect policy outcomes through unobservable actions such quid pro quo purchases of legislative votes, legislative pressure on regulatory agencies (Snyder 1990), as well as buying access for an opportunity to make the firm's concerns known to legislators directly (Hall and Wayman 1990). Ultimately, under the theory of political investment, the final result of the politician's actions will be to increase the firm's future revenue or profitability.

[4] Please see Section 4 for a detailed explanation of how political contributions serve to measure political connections.

If the market views the firm's political contributions as an investment with positive net present value, there should be a positive relation between political contributions and future returns. Indeed, Cooper et al. (2010) find that political contributions are positively related to future stock returns and future operating performance. The authors develop a new measure of political connectedness by using the number of politicians to whom a firm makes political contributions. In addition, Claessens et al. (2008) find that Brazilian firms that made political contributions experienced higher stock returns around the 1998 and 2002 elections than firms that did not make contributions. However, other studies find an adverse effect of political contributions. For example, Aggarwal et al. (2012) find a negative relation between the *amount* of campaign contributions and future stock returns. They also show that firms which contribute have worse corporate governance and conclude that political donations are symptomatic of agency problems.

Although the majority of studies on political contributions rely on the theory of political investment, most studies find only weak, or no evidence, that contributions affect policy. Tullock's (1972) puzzle seeks to determine why there is so little money in U.S. politics. If political contributions are made with the intent of earning a rate of return and the value of public policy has significant worth to corporations, Tullock argues that firms would want to give exponentially more money to politicians (soft money loopholes have traditionally been available even if PAC contributions were to reach the legal limit). Hart (2001) points out that we still know very little about why some firms choose to make campaign contributions and others do not, and why some firms give a lot while others give a little. In addition, the investment in political capital motivation raises the concern of an "undemocratic exchange of policy for dollars" (Gordon et al. 2007). The authors point out that even if this exchange exists it will be difficult to detect because the politicians will conceal their actions for fear of being exposed.

There has been only weak evidence that political contributions have an effect on the voting behavior of members of Congress. Ansolabehere et al. (2003) summarize the results of 40 studies that examine the connection between campaign contributions and congressional voting behavior. They find that most studies report either weak or insignificant results and conclude that "contributions explain a miniscule fraction of the variation in voting behavior in the U.S. Congress". However, using legislators' roll-call votes as a measure of favor-granting often leads to significant measurement error (De Figueiredo and Edwards 2007). First, the true dependent variable is policy outcomes, not voting behavior. Legislators can provide access to the policy-making process or influence over regulatory bodies instead of providing votes. Since voting is a very public and transparent forum, many politicians would not be likely to grant favors to firms through voting in exchange for political contributions. Second, the purchase of roll-call votes would imply a mechanical, political spot market. However, relationships between politicians and firms tend be long-term in nature and favors are usually granted as the opportunity arises during the legislator's term in office (Snyder 1992). Third, there is likely an endogeneity problem because political contributions can influence votes, but votes can also influence contributions.

A recent study by De Figueiredo and Edwards (2007) overcomes many of these issues by examining the effect of state-level campaign contributions by telecommunications companies on regulatory policy decisions of state public utility commissions. They show that contributions to state legislators significantly affect policy outcomes. The authors thus provide strong evidence supporting the political investment theory by using a direct measure of policy impact instead of noisy measures traditionally used in the literature such as roll-call votes by legislators.

The alternative competing theory proposes that political contributions are a form of consumption and not an investment. If this is true, the firm will not have an expectation of being rewarded with favorable legislation in the future. Any money donated by the firm will simply be an expression of individual political participation. Furthermore, some managers will give because they are ideologically motivated, have personal preferences over candidates and parties, or desire to be appointed to cabinet positions or ambassadorships (Aggarwal et al. 2012). Ansolabehere et al. 2003 argue that the theory of consumption is more likely to explain why firms make political contributions since all of the firms' donations ultimately come from individuals. They state that individuals essentially donate because they are ideologically motivated and wish to participate in politics, not because they expect politicians to reciprocate favors to the firm where they are employed. They further show that the amount given is usually very small per individual and per firm and these insignificant donations are not likely to influence politicians. They conclude that the small dollar amounts of political donations which come from many different individuals are not being made to purchase policy.

3. HYPOTHESIS DEVELOPMENT

3.1. The Effect of Political Connections on Recommendation Informativeness

I first analyze whether a firm's political connections impact the informativeness of analysts' stock recommendations. Snyder (1992) finds that political contributions are more reflective of long-term investments rather than short-term, quid pro quo investments. He shows that firms tend to donate to the same politicians over time, to younger representatives, and to candidates running for offices that are "stepping stones" to higher offices which are more influential. The long-term relationships between firms and politicians often manifest into political favors for the donating firms as opportunities arise during the legislator's tenure in office. For example, studies find that politically connected firms receive preferential access to bank financing (Leuz and Oberholzer-Gee 2006), are awarded more government procurement contracts (Goldman et al. 2012), and are more likely to receive a government bailout in times of financial distress (Faccio et al. 2006). Other studies find that political connectedness is directly related to firm valuation. Faccio (2006) uses an international sample of firms and finds that there is an increase in firm value at the announcement of officers or large shareholders entering politics. In addition, Faccio and Parsley (2009) find a 1.7% decline in firm value for companies headquartered in the town of a politician who has died unexpectedly. These studies provide strong evidence that political connections matter for investors.

However, it is difficult for analysts to be able to predict the favorable effects of political connections over the short-term through earnings forecasts due to uncertainty regarding the timing of politicians' actions and the legislative process. On the other hand, analysts' stock recommendations are issued for longer time horizons and even if analysts cannot anticipate the short-term effects on the subsequent period's earnings, the long-term window of the recommendation should capture the impact of the change in expected future cash flows. Assuming analysts can effectively incorporate the effects of political connections into stock recommendations, this will result in recommendations being more informative to investors. Alternatively, if analysts are unable to use other information to resolve uncertainty effectively, stock recommendations will be less informative. This leads to my first non-directional hypothesis which is H1: Political connections are not related to recommendation informativeness.

3.2. The Effect of Political Connections on Accuracy and Informativeness

Next, I investigate how political connections affect the relation between forecast accuracy and recommendation informativeness. Chen et al. (2010) find that analysts have worse forecast accuracy for firms that are politically connected. This is because it is difficult for analysts to predict the effects of political decisions on firms' future earnings streams. There is also evidence that future earnings volatility is higher for politically connected firms which is consistent with increased uncertainty associated with politicians' actions (Cooper et al. 2010). Since earnings predictability is much lower for firms with political connections, it is possible that analysts will rely less on earnings forecasts in their private valuation models. Accordingly, there will be a lower association between earnings forecast accuracy and recommendation informativeness.

On the other hand, since political relationships between firms and politicians tend to be long-term, experienced analysts will have many years of experience following a politically connected firm. Analysts that have such long-standing relationships with companies will build up very valuable, in-depth knowledge of the firm, quality of management, industry expertise, and firm-specific, idiosyncratic information. Over an analyst's tenure following a firm, the analyst will experience the firm establishing political connections in some years, terminating connections in other years, and strengthening or weakening connections in still other years. Analysts will have the opportunity to learn from the effect of differing degrees of political connections manifesting into political favors which influence future reported earnings. Thus, the analyst's specialized knowledge which has been developed over time should improve forecast accuracy for these types of firms. Therefore, it is possible that analysts who have more experience with politically connected firms or analysts who perform more private information search for these firms will rely more on earnings forecasts in their private valuation models. This will result in a higher association between earnings forecast accuracy and recommendation informativeness. This leads to my second non-directional hypothesis which is H2: Political connections do not affect the consistency between analysts' earnings forecast accuracy and stock recommendation informativeness.

4. POLITICAL CONNECTIONS MEASUREMENT

4.1. Political Contributions

Firms that would like to contribute to federal candidates and political parties are required by the Federal Election Campaign Act of 1974 (FECA) to create political action committees (PACs). Firms are allowed to pay for the start-up, overhead, and fundraising expenses of the PAC but cannot give funds from the treasury to the PAC for the purpose of contributing to a federal candidate. PAC contributions are mainly donated by the firm's managers. In my sample, 11.8% of publicly traded firms have PACs. Approximately, one-third of all industries do not have any firms with PACs. PACs are allowed to make direct contributions to candidates, also called "hard money" contributions.[5] In addition, PACs cannot give more than $10,000 in a 2-year election cycle to any particular candidate.

Corporate political contributions have been used extensively in the prior literature to measure political connections for several reasons (Myers 2005). First, firms have been required to file publicly available, detailed information with the FEC since 1979 on their political contributions made through their PACs. Second, since firms must report the amount of money given by the PAC and the identity of the receiving political candidate, the firm-candidate relationship is a direct and powerful measure of a political connection. The Lobby Reform Act of 1995 also requires firms to disclose all expenditures on executive and legislative lobbying. Even though firms spend about ten times more on lobbying than on PAC contributions, lobbying expenses usually cannot be attributed to any politician directly, and thus are indirect measures of

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[5] Firms have also been able to make "soft money" donations directly to political parties for non-partisan party-building activities and issue advertising which does not specifically name political candidates. The Bipartisan Campaign Reform Act of 2002 banned soft money contributions. However, in 2010, the ruling on Citizens United v. Federal Election Commission ended the ban on soft money, and firms are now able to provide unlimited funds to support or oppose political candidates to Super PACs. For issues related to campaign finance reform at the state level see Gross and Goidel (2003).

political connections. Third, political contributions are highly correlated with other forms of political activity such as lobbying and soft money expenditures. For example, Bertrand et al. (2011) analyze individual lobbyists' political contributions and find a strong correlation with their client firms' contributions. Furthermore, they show that lobbyists systematically switch issues as the politicians to which they make political contributions switch committee assignments. Therefore, PAC contributions serve as a strong indicator of a political connection.

I follow Cooper et al. (2010) and design my measures of political connections based on the number of supported candidates. They argue that if hard money contributions are correlated with other ways in which the firm establishes relationships with politicians, the number of politicians that a firm supports is a good proxy for a firm's political involvement. Additionally, Ansolabehere et al. (2003) state that only 4% of all PAC contributions are at or near the $10,000 FEC limit and the average PAC contribution is only $1,700. Therefore, since PAC contributions are not binding and the limit is an immaterial amount to the firm, it is not the dollar amount of the contribution that matters but rather to whom the connection is made.

4.2. Measures using Political Contributions

The main measure of political connections, following Cooper et al. (2010), is:

$$CANDIDATES_t = \sum_{j=1}^{J} Candidates_{jt} \qquad (1)$$

$Candidates_{jt}$ is equal to one if the firm has contributed to candidate j in year t. $POLITICAL^{Candidates}$ equals 1 if $CANDIDATES$ is greater than the industry-year mean, and 0 otherwise.

I also use the authors' three alternative measures to create more refined and powerful measures of political connections. The second proxy weighs equation (1) by factors related to the strength of the relationship between the firm and the candidate. This is because firms tend to build relationships with politicians over long periods of time (Snyder 1992). To capture the strength of the relationship, I estimate the following equation:

$$STRENGTH_t = \sum_{j=1}^{J} Candidates_{jt} \times I_{jt} \times \frac{NCV_{jt}}{NOV_{jt}} \times rellength_{jt} \qquad (2)$$

Candidates$_{jt}$ is equal to one if the firm has contributed to candidate *j* over in year *t*. Incumbents are more likely to have a greater number of corporate contributors and receive a greater dollar amount of contributions (Snyder 1990, Gross and Goidel 2003). Therefore, I include I_{jt} as equal to one if the candidate is incumbent at time *t*, and 0 otherwise. The ratio $\frac{NCV_{jt}}{NOV_{jt}}$ captures the strength of the candidate's party in relation to the opposing party. NCV_{jt} is the number of votes that candidate *j*'s party holds in office at time *t*. NOV_{jt} is the number of votes that candidate *j*'s opposing party holds in office at time *t*, and $rellength_{jt}$ is the number of continuous months of the firm-candidate relationship. $POLITICAL^{Strength}$ equals 1 if *STRENGTH* is greater than the industry-year mean, and 0 otherwise.

The third proxy weighs equation (1) by factors related to the ability of the candidate to help the firm. Specifically, the ability of the politician to assist the firm increases significantly if the firm is located in the same state or district (Kroszner and Stratmann 1998). To capture the ability of the politician to help the firm, I estimate the following equation:

$$ABILITY_t = \sum_{j=1}^{J} HomeCandidate_{jt} \times I_{jt} \times \frac{NCV_{jt}}{NOV_{jt}} \qquad (3)$$

$HomeCandidate_{jt}$ is equal to one if the firm has contributed to candidate *j* in year *t* and the firm is headquartered in the same state in which the candidate is running for office. All other variables are defined above. $POLITICAL^{Ability}$ equals 1 if *ABILITY* is greater than the industry-year mean, and 0 otherwise.

The fourth proxy weighs equation (1) by factors related to the power of the candidate. This is because the prior literature shows that politicians who are committee chairs or serve on powerful committees receive more contributions than other politicians (Grier and Munger 1991). To capture the power of the politician, I estimate the following equation:

$$POWER_t = \sum_{j=1}^{J} Candidates_{jt} \times I_{jt} \times \frac{NCV_{jt}}{NOV_{jt}} \times \left[\sum_{m=1}^{M} \frac{Rank_{mt}}{Median\ Rank_{mt}}\right]_j \quad (4)$$

$Rank_{mt}$ is the reciprocal of candidate *j*'s rank on committee *m* (where rank =1 for the most important member, rank = 2 for the next important member, etc.). $Median\ Rank_{mt}$ is the median number of members on committee *m*. All other variables are defined above. $POLITICAL^{Power}$ equals 1 if *POWER* is greater than the industry-year mean, and 0 otherwise.

5. RESEARCH DESIGN

5.1. Benchmark Model of Recommendation Informativeness

To examine the relation between forecast accuracy and recommendation informativeness, I follow Ertimur et al. (2007) and first estimate the following benchmark model for the pooled sample of all stock recommendations and earnings forecasts:

$$RET = \alpha_0 + \alpha_1 PMAFE + \alpha_2 FIRMEXP + \alpha_3 BSIZE + \alpha_4 N\_FIRMS + \alpha_5 REC\_FREQ + \alpha_6 LFR + \alpha_7 N\_ANALYSTS + \alpha_8 REG + \varepsilon \qquad (5)$$

For expositional purposes, analyst, firm, forecast, and year subscripts are omitted. I measure forecast accuracy, *PMAFE*, as the relative forecast accuracy which compares an analyst's absolute forecast error to the mean absolute forecast error of all analysts following the firm (Clement 1999) as described below:

$$PMAFE = -1 \times \frac{AFE_{ijk} - \overline{AFE}}{\overline{AFE}},$$

where AFE_{ijk} is the absolute forecast error for earnings forecast *k* that analyst *i* issues for firm *j* and $\overline{AFE}$ is the mean absolute forecast error for firm *j*. Clement (1999) shows that this measure of relative accuracy controls for firm-year effects and reduces heteroskedasticity in forecast error distributions across firms. The equation is multiplied by -1 so that higher values of PMAFE connote higher levels of accuracy. I expect α_1 to be positive and significant consistent with the prior literature which finds a positive relation between accuracy and informativeness (Loh and Mian 2006, Ertimur et al. 2007).

Recommendation informativeness, *RET*, is the market-adjusted return to recommendation *k* made by analyst *i* for firm *j*. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, \$1 is invested (shorted) in the recommended stock. Firm experience, *FIRMEXP*, is the number of years through year *t* for which analyst *i* supplied forecasts for firm *j*. Brokerage firm size, *BSIZE*, is the logarithm of the number of analysts employed by the brokerage that analyst *i* works for during year *t*. Number of firms, *N_FIRMS*, is the number of firms for which analyst *i* issues annual forecasts during the year in which the recommendation is made. Recommendation frequency, *REC_FREQ*, is the number of recommendations analyst *i* issues for firm *j* during year *t*. Leader-follower ratio, *LFR*, is the cumulative number of days by which the preceding two forecasts lead forecast *k* divided by the cumulative number of days by which the subsequent two forecasts follow forecast *k* following Cooper et al. (2001). Number of analysts, *N_ANALYSTS*, is the number of analysts who issue forecasts and recommendations for firm *j* during year *t*. Regulated industry, *REG*, equals 1 if the firm operates in the financial services industry (one-digit SIC code 6) or in the utilities industry (two-digit SIC code 49), and 0 otherwise.

5.2. The Effect of Political Connections on Accuracy and Informativeness

Next, I examine how political connections affect recommendation informativeness as well as the relation between accuracy and informativeness. I supplement the benchmark model with the political connections proxy and the interaction between political connections and forecast accuracy:

$$\begin{aligned} RET = {} & \beta_0 + \beta_1 POLITICAL_i + \beta_2 PMAFE + \beta_3 PMAFE*POLITICAL_i + \beta_4 FIRMEXP \\ & + \beta_5 BSIZE + \beta_6 N\_FIRMS + \beta_7 REC\_FREQ + \beta_8 LFR + \beta_9 N\_ANALYSTS \\ & + \beta_{10} REG + \varepsilon \qquad (6) \end{aligned}$$

$POLITICAL_i$ is one of four proxies for political connections. Following Cooper et al. (2010), I use the following constructs to design measures for political connectedness: (1) *CANDIDATES* is the number of supported candidates, (2) *STRENGTH* is the number of supported, incumbent candidates weighted by the length of the firm-candidate relationship, (3) *ABILITY* is the number of supported, incumbent candidates that hold office in the same state where the firm is headquartered, and (4) *POWER* is the number of supported, incumbent candidates weighted the power of the candidate. $POLITICAL_i$ equals 1 if the measure is greater than the industry-year mean, and 0 otherwise. See Section 4 for details on variable construction.

6. DATA AND MEASUREMENTS

6.1. Sample Selection

The sample uses the Compustat annual database, CRSP daily stock prices, I/B/E/S detail history file, and I/B/E/S detail recommendations file from 1993 – 2011. The sample begins in 1993 because this is the first year stock recommendations are made available in I/B/E/S. Every recommendation is matched to an annual earnings forecast from the same analyst and the same firm during the 30-day period prior to and including the issue date of the recommendation. Firm-years must have at least three analysts following the firm to remain in the sample because my accuracy measure for an analyst is relative to the average accuracy of all other analysts following the firm (Clement 1999).

For political contribution data, I obtain the database of the Federal Election Commission (FEC) filings through the Center for Responsive Politics. This database contains all corporate political action committee (PAC) donations to individual political candidates running for federal office in the House of Representatives, Senate, and Presidency. I do not obtain political contributions from individuals, labor organizations, trade organizations, party committees, private companies, or subsidiaries of foreign firms because these sources of monetary influence are not related to the firm's PAC. To calculate a candidate's committee ranking, I acquire data on House and Senate committee assignments and rankings from Charles Stewart's Congressional Data Page.[6]

I manually match the names of firms provided by the FEC database to CRSP company names. I successfully match approximately 56% of 1,820 PAC corporate names to CRSP data and about 80% of the dollar amount of contributions. This is consistent with Grier et al. (1994) who match 50 - 60% of names and 80% of contributions. After using the SEC's EDGAR

[6] I thank Charles Stewart for providing access to this data (http://web.mit.edu/17.251/www/data_page.html).

database to properly match companies with name changes, I obtain 809,334 political contributions from 1,019 unique firms. The former figure includes multiple contributions to some of the same candidates. These contributions are spread over 8,901 different political candidates. After merging the FEC database with I/B/E/S and CRSP, I obtain 261,295 analyst-firm-year observations representing 8,641 unique firms.

6.2. Descriptive Statistics

Panel A and Panel B of Table 1 reports the descriptive statistics for financial analyst characteristics for the full sample of firms. In Panel A, the mean abnormal return to stock recommendations is 6.0% over the 30 day measurement period. Approximately 74.8% of the recommendations lead to positive abnormal returns. The mean (median) of *PMAFE* is 0.012 (0.111). Analysts have approximately 3 years of firm-specific experience, follow 16 different companies, and issue about 2 recommendations per year for the firms they cover. The average brokerage firm in the sample employs 57 analysts. Analyst coverage is approximately 13 analysts per firm. Of the total 8,641 firms in the sample, 1,019 (11.8%) firms have political contributions and 7,622 (88.2%) firms do not have contributions.

Panel B of Table 1 provides the descriptive statistics comparing firms that make political contributions to firms that do not make such contributions using propensity-matched scoring. I create a matched sample based on the predicted probabilities from the 1st stage probit regression presented in Appendix B. The propensity score matching procedure produces a matched sample of 33,132 control observations leading to a combined sample of 66,264 observations. Analysts of firms that contribute have less informative recommendations (4.7%) than analysts of firms that do not contribute (5.6%). However, there is no difference in analysts' forecast accuracy for contributors versus non-contributors. Analysts that follow firms that contribute tend to have

Table 1
Descriptive Statistics
Financial Analyst Characteristics

Panel A: Descriptive Statistics for the Pooled Sample

Variable	N	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
RET	261,295	0.060	0.151	(0.944)	0.002	0.046	0.114	7.609
Fraction of positive RET	261,295	0.748	-	-	-	-	-	-
PMAFE	261,295	0.012	0.685	(2.580)	(0.399)	0.111	0.567	1.000
FIRMEXP	261,295	3.121	2.953	1.000	1.000	2.000	4.000	29.000
BSIZE	261,295	57.041	49.332	1.000	18.000	40.000	84.000	247.000
N_FIRMS	261,295	15.799	10.483	1.000	10.000	14.000	19.000	114.000
REC_FREQ	261,295	1.875	1.950	1.000	1.000	1.000	2.000	66.000
LFR	261,295	2.856	8.364	0.002	0.415	1.000	2.484	376.000
N_ANALYSTS	261,295	13.134	8.271	3.000	6.000	11.000	18.000	52.000
REG	261,295	0.171	0.376	0.000	0.000	0.000	0.000	1.000

Panel B: Descriptive Statistics by Political Involvement (Propensity Score Matching)

	POLITICAL CONTRIBUTORS			NON-CONTRIBUTORS			
Variable	**Mean**	**Median**	**Std Dev**	**Mean**	**Median**	**Std Dev**	**Difference in Means**
RET	0.047	0.038	0.108	0.056	0.044	0.124	(0.008) ***
Fraction of positive RET	0.762	-	-	0.758	-	-	0.004
PMAFE	0.021	0.164	0.859	0.016	0.157	0.837	0.005
FIRMEXP	4.013	3.000	3.672	3.493	2.000	3.220	0.520 ***
BSIZE	61.220	49.000	50.105	64.141	50.000	51.987	(2.921) ***
N_FIRMS	17.448	15.000	12.733	15.544	14.000	10.479	1.903 ***
REC_FREQ	1.944	1.000	2.389	1.919	1.000	2.306	0.025
LFR	2.525	1.000	6.212	2.665	1.000	6.934	(0.140) ***
N_ANALYSTS	18.069	17.000	8.686	15.245	14.000	8.250	2.824 ***
REG	0.180	0.000	0.384	0.113	0.000	0.317	0.067 ***

There are 261,295 observations estimated over 1993 - 2011. RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise. Propensity scores are calculated using the 1st Stage Probit model in Appendix B and results in 66,264 observations for the combined treatment and control groups.

more years of firm-specific experience (4.0) and cover more companies (17.4) than analysts who follow firms that do not contribute (3.5 and 15.5, respectively). In addition, analysts who cover contributors tend to work at brokerage firms that employ fewer analysts (61.2) and tend to have less timely forecasts (2.5) than analysts who cover non-contributors (64.1 and 2.7, respectively). The number of analysts following a political contributor (18.1) is significantly larger than the number of analysts following a non-contributor (15.2) which is consistent with contributing firms being the largest publicly-traded firms. Lastly, the percentage of firms that analysts cover which are in a regulated industry is significantly larger for contributors (18.0%) than for non-contributors (11.3%).

Panel A of Table 2 report the descriptive statistics for the political contributions that firms make. The average firm donates $117,360 in total political contributions during any 2-year election cycle. Total political contributions range from $5 to $3,827,600. Firms make approximately 93 political contributions during any 2-year election cycle although the maximum is 2,074 contributions. Firms support anywhere between 1 and 518 candidates every election cycle, with the average firm supporting 35 candidates. Although there is much variation in the number of candidates that some firms support cross-sectionally, there is little variation on a per-firm basis in the number of supported candidates over time.

Firms donate about $3,353 per candidate per election cycle ($117,360/35 candidates). Interestingly, Cooper et al. (2010) report an average of $2,086 per candidate from total mean contributions of only $64,694 and 31 supported candidates over the period 1979 - 2004. Therefore, firms are still not constrained by the FEC contributions limit which is $10,000 per candidate over an election cycle. Even though firms are contributing significantly more in total dollar amounts, they are supporting a similar number of candidates per election cycle. It is possible the larger amounts of money being donated are reflective of the benefits that firms expect to obtain from connections to politicians which would be supportive of the theory of investment in political capital.

Table 2
Firm Political Contributions Descriptive Statistics

Panel A: Political Contributions Statistics

Variable	Mean	Min	Q1	Median	Q3	Max
Total Contributions	$117,360	$5	$11,000	$35,499	$115,100	$3,827,600
Number of Contributions	93	1	11	33	104	2,074
Number of Candidates	35	1	5	16	44	518

Panel B: Political Contributions by Largest Industry Contributors

		Amount of Political Contributions			Number of Supported Candidates		
	Industry	Republican	Democratic	Total	Republican	Democratic	Total
1)	*Financial*	$5,551,825	$3,474,692	$9,026,517	2,411	1,567	3,978
2)	*Utilities*	3,571,199	2,340,800	5,911,999	1,678	1,123	2,801
3)	*Telecommunications*	3,099,786	2,263,322	5,363,108	1,058	852	1,910
4)	*Transportation*	3,324,755	1,827,245	5,152,000	1,010	677	1,687
5)	*Pharmaceutical Products*	2,828,821	1,783,923	4,612,744	1,066	723	1,789
6)	*Petroleum and Natural Gas*	2,761,201	736,980	3,498,181	1,345	425	1,770
7)	*Electronic Equipment*	1,920,415	1,385,532	3,305,947	520	235	755
8)	*Machinery*	1,759,068	961,687	2,720,755	705	390	1,095
9)	*Retail*	1,793,140	893,820	2,686,960	780	419	1,199
10)	*Business Services*	1,304,083	1,121,505	2,425,588	654	532	1,186

This table reports the total federal political contributions for the top 10 donating firms over the period 1993-2011. Data is obtained from the Federal Election Commission (FEC) through the Center for Responsive Politics on political contributions to House, Senate, and Presidential elections. Data are excluded from all noncorporate contributions, contributions from private firms and subsidiaries of foreign firms. The sample includes 809,334 contributions made by 1,019 unique firms. The table reports firm contribution characteristics per firm, per election cycle.

Panel B of Table 2 reports political contributions by the ten largest industry contributors based on the Fama-French (1997) 49 industry classification[7]. Consistent with Aggarwal et al. (2012), the top contributors are financial/banking, utilities, telecommunications, and transportation. In line with Republicans traditionally receiving higher total dollar contributions per firm than Democrats, every industry donates significantly more to the Republican party than to the Democratic party. Prior to 2004, the financial industry gave approximately 55% of their total contributions to Republicans. Since this time period, however, the industry has actually donated a slight majority of their contributions to the Democratic party. All of the industries support a greater number of Republican candidates than Democratic candidates.

Table 3 reports the Pearson correlations for the full sample. The correlation between political contributions (*POLITICAL*) and informativeness (*RET*) is -0.053 indicating that when a firm has more connections to politicians, analysts' recommendations are less informative. Political contributions (*POLITICAL*) and forecast accuracy (PMAFE) are positively related, 0.004, and is significant at the 5% level. Forecast accuracy (*PMAFE*) and informativeness (*RET*) have a positive and significant correlation, 0.026, consistent with the prior literature. There is a positive correlation between informativeness (*RET*) and brokerage firm size of 0.030, recommendation frequency of 0.008, and forecast timeliness of 0.037. There is also a negative correlation between informativeness (*RET*) and both the number of firms followed of -0.013 and analyst coverage of -0.047. The majority of the correlations among the independent variables are statistically significant but their magnitudes are not large.This suggests that multicollinearity should not be of concern. I investigate the issue of multicollinearity further by calculating the Variance Inflation Factors (VIF) in all multivariate regressions that follow.

[7] Banking, Insurance, and Trading are all included in "Financial" because the Center for Responsive Politics generally aggregates these industries when reporting the largest source of campaign contributions to federal candidates and parties.

Table 3
Pearson Correlations

	RET	*POLITICAL*	*PMAFE*	*FIRMEXP*	*BSIZE*	*N_FIRMS*	*REC FREQ*	*LFR*	*N_ANALYSTS*
RET									
POLITICAL	-0.053								
PMAFE	0.026	0.004^							
FIRMEXP	0.001#	0.075	-0.001#						
BSIZE	0.030	0.014	0.014	0.031					
N_FIRMS	-0.013	-0.036	-0.011	0.164	0.022				
REC FREQ	0.008	0.014	-0.006	0.057	-0.042	0.077			
LFR	0.037	-0.025	0.045	-0.001#	0.021	-0.005	-0.005		
N_ANALYSTS	-0.047	0.289	0.020	0.208	0.034	0.042	0.020	-0.051	
REG	-0.029	-0.088	0.001#	0.019	0.016	0.185	-0.025	0.000#	-0.017

All correlations are significant at the 1% level except those marked with a "#" which are not significant, those with a "!" which are significant at the 10% level, and those with a "^" which are significant at the 5% level. There are 261,295 observations estimated over 1993 - 2011. RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL equals 1 if politically connected based on the measure $\text{POLITICAL}^{\text{Candidates}}$, and 0 otherwise. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

7. EMPIRICAL ANALYSES

7.1. Benchmark Regression of Recommendation Informativeness

In Table 4, I first report the results of the relation between forecast accuracy and recommendation informativeness using the benchmark model from Ertimur et al. (2007). As expected, there is a significantly positive relation between informativeness and accuracy (*PMAFE* = 0.0034) indicating that analysts who have more accurate earnings forecasts tend to have more informative stock recommendations. The results also indicate that analysts with more years of firm-specific experience have more informative recommendations (*FIRMEXP* = 0.0005). Furthermore, informativeness increases with brokerage firm size (*BSIZE* = 0.0001), recommendation frequency (*REC_FREQ* = 0.0005), and earnings forecast timeliness (*LFR* = 0.0006) as expected. However, informativeness decreases when analyst following is greater (*N_ANALYSTS* = -0.0008) and when firms are in a regulated industry (*REG* = -0.0128).

7.2. Main Political Connections Regression

Table 5 presents the main results of the study which address hypotheses 1 and 2. In column 1, the proxy for political connections (*POLITICAL*) is based on the number of supported candidates. There is a negative and significant relation between recommendation informativeness (*RET*) and political connections (*POLITICAL*) of -1.1867. This indicates that analysts appear to be unable to use other information in an efficient manner to resolve the uncertainty associated with political connections. There is also a negative and significant relation between informativeness (*RET*) and the interaction of accuracy and political connections (*PMAFE*POLITICAL*) of -0.3837. This signifies that analysts rely less on earnings forecasts in private valuation models used in generating stock recommendations for politically connected firms due to these types of firms having greater earnings uncertainty.

Table 4
Relation between Accuracy and Informativeness - Benchmark Model

$$RET = \alpha_0 + \alpha_1 PMAFE + \alpha_2 FIRMEXP + \alpha_3 BSIZE + \alpha_4 N\_FIRMS + \alpha_5 REC\_FREQ + \alpha_6 LFR + \alpha_7 N\_ANALYSTS + \alpha_8 REG + \varepsilon$$

	Coefficient		Std. Error	*t*-statistic
Intercept	0.0547	***	0.0013	40.91
PMAFE	0.0034	***	0.0003	10.33
FIRMEXP	0.0005	***	0.0001	4.90
BSIZE	0.0001	***	0.0000	11.34
N_FIRMS	0.0000		0.0000	0.93
REC_FREQ	0.0005	***	0.0002	3.50
LFR	0.0006	***	0.0000	16.94
N_ANALYSTS	-0.0008	***	0.0000	-22.06
REG	-0.0128	***	0.0008	-16.13
R^2	1.50%			
Year Dummies	included			

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 261,295 observations estimated over 1993 - 2011.
RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

Informativeness (*RET*) is positively and significantly related to forecast accuracy (*PMAFE* = 0.3850) indicating that, on average, analysts use their earnings forecasts in generating stock recommendations. Analysts who work at larger brokerage firms (*BSIZE* = 0.0071), issue more recommendations in a given year (*REC_FREQ* = 0.0551), and have more timely forecasts relative to other analysts following the same firm (*LFR* = 0.0592) tend to have more informative recommendations. On the other hand, analysts who cover firms that have a larger analyst following (N_ANALYSTS = -0.0680) or are in a regulated industry (REG = -1.2111) tend to have less informative recommendations.

The main results are consistent across the other three more powerful measures of political connections. In column 2, the proxy for political connections is based on the strength of the firm-candidate relationship (*STRENGTH*). The proxy in column 3 is based on the number of "same-state" candidates (*ABILITY*). Lastly, the proxy in column 4 is based on the number of candidates weighted by the power of the candidates (*POWER*). All three of the alternative political connection proxies have a negative and significant relation with recommendation informativeness (-1.4166, -0.6708, and -1.3041, respectively). In addition, for all of the political connections proxies there is a negative and significant relation between informativeness and the interaction of accuracy and political connections (-0.3731, -0.3194, and -0.3794, respectively). Since these more refined measures take into the strength of the relationship, the ability of the candidate to help the firm, and the power of the candidate, they provide additional reinforcement that analysts' forecasts are less consistent with recommendations when the firms they follow have political connections.

Table 5
The Effect of Political Connections on the Relation between Accuracy and Informativeness

$$RET = \beta_0 + \beta_1 POLITICAL + \beta_2 PMAFE + \beta_3 PMAFE*POLITICAL + \beta_4 FIRMEXP + \beta_5 BSIZE + \beta_6 N\_FIRMS + \beta_7 REC\_FREQ + \beta_8 LFR + \beta_9 N\_ANALYSTS + \beta_{10} REG + \varepsilon$$

	Candidates	Strength	Ability	Power
Intercept	5.3562 ***	5.2477 ***	5.8611 ***	5.2461 ***
POLITICAL	-1.1867 ***	-1.4166 ***	-0.6708 ***	-1.3041 ***
PMAFE	0.3850 ***	0.3763 ***	0.4082 ***	0.3796 ***
*PMAFE*POLITICAL*	-0.3837 ***	-0.3731 ***	-0.3194 ***	-0.3794 ***
FIRMEXP	0.0596 ***	0.0603 ***	0.0571 ***	0.0597 ***
BSIZE	0.0071 ***	0.0071 ***	0.0071 ***	0.0071 ***
N_FIRMS	0.0025	0.0028	0.0020	0.0027
REC_FREQ	0.0551 ***	0.0541 ***	0.0543 ***	0.0553 ***
LFR	0.0592 ***	0.0592 ***	0.0592 ***	0.0593 ***
N_ANALYSTS	-0.0680 ***	-0.0673 ***	-0.0719 ***	-0.0670 ***
REG	-1.2111 ***	-1.2011 ***	-1.2503 ***	-1.2057 ***
R^2	1.63%	1.63%	1.60%	1.63%
Year Dummies	included	included	included	included

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 261,295 observations estimated over 1993 - 2011.

The 4 columns in this table use 4 different proxies for political connections (POLITICAL): Candidates, Strength, Ability, and Power. POLITICAL equals 1 if politically connected, 0 otherwise. See Appendix A for variable definitions. RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL is the number of supported candidates by firm j in year t. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

8. SENSITIVITY AND ADDITIONAL ANALYSES

8.1. Two-Stage Heckman Selection Model

In this section I address potential endogeneity problems due to selection bias. Since the firm has to decide to establish a political action committee and make political contributions, the results in the main tests have potential bias. I use the following first-stage probit model based off Cooper et al. (2010) to estimate the probability that a firm will make political contributions:

$$\begin{aligned} ACTIVE = {} & \lambda_0 + \lambda_1 SIZE + \lambda_2 SALES + \lambda_3 EMPLOYEES + \lambda_4 BUS\_SEG + \lambda_5 GEO\_SEG \\ & + \lambda_6 BM + \lambda_7 LEV + \lambda_8 CFO + \lambda_9 MARKET\_SHARE + \lambda_{10} HERF \\ & + \lambda_{11} REG + \lambda_{12} INDUSTRY\_ACTIVE + \varepsilon \qquad (7) \end{aligned}$$

Since the choice of exclusion restrictions is important in executing the selection model and controlling for endogeneity, I utilize the number of employees in the determinants model as the primary exclusion restriction. Political action committees (PACs) are established by the firm but the contributions come entirely from employees, not company resources. Prior studies find that firms with more employees are more likely to have a PAC (Grier et al. 1994). This is because PAC contributions have to be raised from employees in sufficient quantities for the PAC to be effective in its objectives. Furthermore, firms with more employees are better able to pay the fixed start-up and accounting costs for establishing a PAC. Therefore, the number of employees is an important determinant of being politically active in the 1^{st} stage model. There is no economic rationale which would suggest that the number of employees at the firm that the analyst covers should be significantly related to the recommendation informativeness (the dependent variable in the 2^{nd} stage).

In model (7) above, *ACTIVE* equals 1 if the firm has a political action committee, 0 otherwise. *SIZE* is the natural logarithm of market value of equity. *SALES* is the natural logarithm of sales. *EMPLOYEES* is the natural logarithm of the number of employees. *BUS_SEG* is the number of business segments. *GEO_SEG* is the number of geographic segments. *BM* is book-to-market ratio. *LEV* is the sum of long-term debt and debt in current liabilities, divided by total assets. *CFO* is operating cash flow divided by total assets. *MARKET_SHARE* is sales divided by total industry sales. *HERF* is the Herfindahl index of industry concentration computed with net sales. *REG* equals 1 if the firm operates in the financial services industry (one-digit SIC code 6) or in the utilities industry (two-digit SIC code 49), and 0 otherwise. *INDUSTRY_ACTIVE* is the number of firms in a firm's industry with an established political action committee. The results of the first-stage probit model are included in Appendix B.

The inverse Mills ratio computed from the probit selection in equation (7) is included in the recommendation informativeness regression below.

$$PFT = \gamma_0 + \gamma_1 POLITICAL + \gamma_2 PMAFE + \gamma_3 PMAFE*POLITICAL + \gamma_4 FIRMEXP + \gamma_5 BSIZE + \gamma_6 N\_FIRMS + \gamma_7 REC\_FREQ + \gamma_8 LFR + \gamma_9 N\_ANALYSTS + \gamma_{10} REG + \gamma_{11} MILLS + \varepsilon \quad (8)$$

Table 6 provides the results of the relation between political connections, forecast accuracy, and informativeness after correcting for self-selection. Overall, the negative relation between political connections and informativeness (γ_1) is consistent with main results of the paper. The negative relation between informativeness and accuracy when firms are politically connected (γ_3) is also robust under the political connection specifications. I also examine whether multicollinearity exists in the 2nd stage model by calculating Variance Inflation Factors (VIFs) for all the independent variables. None of the VIFs, including the Mills ratio, exceed 1.72 which suggests that multicollinearity is not likely to be a problem in the test design.

Table 6
Two-Stage Heckman Selection Model Sensitivity Analysis

$$RET = \gamma_0 + \gamma_1 POLITICAL + \gamma_2 PMAFE + \gamma_3 PMAFE*POLITICAL + \gamma_4 FIRMEXP + \gamma_5 BSIZE + \gamma_6 N\_FIRMS + \gamma_7 REC\_FREQ + \gamma_8 LFR + \gamma_9 N\_ANALYSTS + \gamma_{10} REG + \gamma_{11} MILLS + \varepsilon$$

	Candidates	Strength	Ability	Power
Intercept	0.6280 ***	0.7600 ***	0.7214 ***	0.7542 ***
POLITICAL	-0.4035 ***	-0.5821 ***	-0.0662	-0.5137 ***
PMAFE	0.4043 ***	0.3887 ***	0.4247 ***	0.4014 ***
*PMAFE*POLITICAL*	-0.4524 ***	-0.3807 ***	-0.3382 ***	-0.4887 ***
FIRMEXP	0.0737 ***	0.0803 ***	0.0785 ***	0.0800 ***
BSIZE	0.0106 ***	0.0106 ***	0.0107 ***	0.0106 ***
N_FIRMS	0.0059 *	0.0063 *	0.0061 *	0.0064 *
REC_FREQ	0.0442 ***	0.0503 ***	0.0503 ***	0.0505 ***
LFR	0.0579 ***	0.0579 ***	0.0578 ***	0.0579 ***
N_ANALYSTS	0.0130 **	0.0114 **	0.0100 *	0.0115 **
REG	0.0067	-0.0187	-0.0295	-0.0168
MILLS	2.0209 ***	1.9254 ***	1.9888 ***	1.9271 ***
R^2	2.07%	2.07%	2.06%	2.07%
Year Dummies	included	included	included	included

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 187,726 observations estimated over 1993 - 2011. See Appendix B for the results of the 1st Stage Probit model.

The 4 columns in this table use 4 different proxies for political connections (POLITICAL): Candidates, Strength, Ability, and Power. POLITICAL equals 1 if politically connected, 0 otherwise. See Appendix A for variable definitions. RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL is the number of supported candidates by firm j in year t. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise. MILLS is the inverse Mills ratio from the first stage probit model in Appendix B. Variance Inflation Factors for all variables are less than 1.72.

8.2. Propensity-Score Matching

In this section, I use propensity-score matching models to further address endogeneity concerns. This is because it is possible the Heckman selection model in the previous section fails to meet the exclusion restriction or because the treatment effects are difficult to estimate due to an underlying nonlinear functional form. Table 7 reports the results of the relation between political connections, forecast accuracy, and informativeness after matching on propensity scores. The results support the negative relation between political connections and informativeness (δ_1) when using all four of the political connection proxies ((number of

Table 7
Propensity Score Matching Sensitivity Analysis

$$RET = \delta_0 + \delta_1 POLITICAL + \delta_2 PMAFE + \delta_3 PMAFE*POLITICAL + \delta_4 FIRMEXP + \delta_5 BSIZE + \delta_6 N\_FIRMS + \delta_7 REC\_FREQ + \delta_8 LFR + \delta_9 N\_ANALYSTS + \delta_{10} REG + \varepsilon$$

	Candidates	Strength	Ability	Power
Intercept	4.4601 ***	4.3930 ***	4.6262 ***	4.4402 ***
POLITICAL	-0.7827 ***	-0.8094 ***	-0.2511 **	-0.7980 ***
PMAFE	0.2091 ***	0.1888 ***	0.2058 ***	0.2000 ***
*PMAFE*POLITICAL*	-0.2220 *	-0.1625	-0.1260	-0.2709 **
FIRMEXP	0.0255 **	0.0254 **	0.0214 *	0.0290 **
BSIZE	0.0061 ***	0.0061 ***	0.0061 ***	0.0065 ***
N_FIRMS	0.0033	0.0035	0.0031	0.0028
REC_FREQ	0.0287	0.0269	0.0262	0.0270
LFR	0.0569 ***	0.0568 ***	0.0570 ***	0.0535 ***
N_ANALYSTS	-0.0378 ***	-0.0385 ***	-0.0411 ***	-0.0394 ***
REG	-0.4621 ***	-0.4615 ***	-0.5180 ***	-0.4491 ***
R^2	1.98%	1.97%	1.92%	1.94%

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 66,264 observations estimated over 1993 - 2011. Propensity scores are calculated using the 1st Stage Probit model in Appendix B.

The 4 columns in this table use 4 different proxies for political connections (POLITICAL): Candidates, Strength, Ability, and Power. POLITICAL equals 1 if politically connected, 0 otherwise. See Appendix A for variable definitions. RET is the market-adjusted return to recommendation *k* made by analyst *i* for firm *j*. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL is the number of supported candidates by firm *j* in year *t*. PMAFE is the difference between the absolute forecast error for analyst *i* for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. FIRMEXP is the number of years through year *t* for which analyst *i* supplied forecasts for firm *j*. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst *i* works for during year *t*. N_FIRMS is the number of firms for which analyst *i* issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst *i* issues for firm *j* during year *t*. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast *k* divided by the cumulative number of days by which the subsequent two forecasts follow forecast *k*. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm *j* during year *t*. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

candidates, strength of firm-candidate relationship, same-state candidates, candidate power). However, the negative relation between informativeness and accuracy when firms are politically connected (δ_3) is only weakly supported. Since it is still not clear why firms make contributions (Hart 2001), it is possible that the first-stage determinants model contains correlated omitted variables which is inducing measurement error in the matching of propensity scores.

8.3. Analyst All-Star Status

Analysts that are selected as All-Stars by *Institutional Investor* tend to have more experience, better reputations, more accurate earnings forecasts, and more informative stock recommendations (Stickel 1992). Therefore, it is possible that the relation between political connections and recommendation informativeness is different for All-Stars compared to non-All-Stars. Since All-Star analysts have lower forecast errors, on average, it is likely they will use their earnings forecasts more efficiently as inputs into valuation models in generating stock recommendations.

In Table 8, I find that the negative relation between political connections and recommendation informativeness (λ_1) holds for both All-Star and non-All-Star analysts. Interestingly, I find that the negative relation between political connections and recommendation informativeness for politically connected firms (λ_3) holds only for non-All-Star analysts as expected. This provides evidence that the inefficiency in transforming accurate earnings into informative recommendations is driven by non-All-Star analysts.

8.4. Recommendation Upgrades vs. Downgrades

Prior work finds that there is a significantly positive (negative) abnormal return associated with stock recommendation upgrades (downgrades) (Stickel 1995, Womack 1996). The authors also find that there is a post-recommendation drift which lasts up to one month for

Table 8
The Effect of Analyst All-Star Status

$$RET = \lambda_0 + \lambda_1 POLITICAL + \lambda_2 PMAFE + \lambda_3 PMAFE{*}POLITICAL + \lambda_4 FIRMEXP + \lambda_5 BSIZE + \lambda_6 N\_FIRMS + \lambda_7 REC\_FREQ + \lambda_8 LFR + \lambda_9 N\_ANALYSTS + \lambda_{10} REG + \varepsilon$$

	All-Star Analysts				Non-All-Star Analysts			
	Candidates	**Strength**	**Ability**	**Power**	**Candidates**	**Strength**	**Ability**	**Power**
Intercept	6.1450 ***	6.1103 ***	7.9959 ***	7.9774 ***	4.7279 ***	4.6787 ***	6.4379 ***	6.3730 ***
POLITICAL	-1.2313 ***	-1.5355 ***	-0.9376 ***	-1.3093 ***	-1.1925 ***	-1.4402 ***	-0.8396 ***	-1.2247 ***
PMAFE	0.2571 **	0.2800 **	0.2439 *	0.1746	0.3988 ***	0.3869 ***	0.4073 ***	0.3810 ***
*PMAFE*POLITICAL*	-0.4815	-0.7092 **	-0.5088 *	-0.3018	-0.3606 ***	-0.3103 **	-0.2982 ***	-0.3997 ***
FIRMEXP	-0.0005	0.0039	-0.0037	-0.0010	0.0764 ***	0.0765 ***	0.0833 ***	0.0800 ***
BSIZE	-0.0014	-0.0014	0.0041 **	0.0039 *	0.0083 ***	0.0082 ***	0.0103 ***	0.0102 ***
N_FIRMS	-0.0144	-0.0147	-0.0274 ***	-0.0275 ***	0.0023	0.0028	-0.0123 ***	-0.0120 ***
REC_FREQ	0.1704 *	0.1648 *	0.1623 *	0.1584 *	0.0493 ***	0.0488 ***	0.0758 ***	0.0805 ***
LFR	0.0661 ***	0.0657 ***	0.0640 ***	0.0640 ***	0.0585 ***	0.0585 ***	0.0588 ***	0.0592 ***
N_ANALYSTS	-0.1029 ***	-0.1002 ***	-0.1022 ***	-0.1006 ***	-0.0654 ***	-0.0647 ***	-0.0765 ***	-0.0764 ***
REG	-0.9890 ***	-0.9637 ***	-0.7992 ***	-0.7551 ***	-1.2195 ***	-1.2102 ***	-1.1770 ***	-1.1495 ***
n	23,023	23,023	23,023	23,023	238,272	238,272	238,272	238,272

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 261,295 observations estimated over 1993 - 2011.

All-Star Analysts are analysts that achieved all-star status at any level as determined by *Institutional Investor* magazine in year t. The 4 columns in this table use 4 different proxies for political connections (POLITICAL): Candidates, Strength, Ability, and Power. POLITICAL equals 1 if politically connected, 0 otherwise. See Appendix A for variable definitions. RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL is the number of supported candidates by firm j in year t. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

upgrades and six months for downgrades. In this section, I test whether the relation between political connections and recommendation informativeness changes when the analyst issues a recommendation upgrade or downgrade.

In Table 9, I find that the negative relation between political connections and recommendation informativeness (σ_1) is robust to both upgrade and downgrade specifications. However, the negative relation between political connections and recommendation informativeness for politically connected firms (σ_3) is more robust for recommendation upgrades than downgrades. It is possible that this analyst inefficiency is worse for recommendation upgrades because upgrades are more likely to be associated with conflicts of interest due to investment banking activities than are downgrades.

8.5. Recommendation Initiations vs. Non-Initiations

McNichols and O'Brien (1997) find evidence of self-selection among analysts in that analysts are more likely to provide coverage for firms about which they have favorable views. They show that recommendation initiations are significantly more optimistic and have higher 1-year-ahead return on equity than non-initiation recommendations. Therefore, I also examine whether the relation between political connections and recommendation informativeness differs when the analysts' recommendation is an initiation or non-initiation.

In Table 10, I find that the negative relation between political connections and recommendation informativeness (ρ_1) holds in both recommendation initiation and non-initiation scenarios. The negative relation between political connections and recommendation informativeness for politically connected firms (ρ_3) appears to be stronger for non-initiation recommendations than initiations. This suggests that analyst experience alone with politically

Table 9
The Effect of Stock Recommendation Upgrades versus Downgrades

$$RET = \sigma_0 + \sigma_1 POLITICAL + \sigma_2 PMAFE + \sigma_3 PMAFE*POLITICAL + \sigma_4 FIRMEXP + \sigma_5 BSIZE + \sigma_6 N\_FIRMS + \sigma_7 REC\_FREQ + \sigma_8 LFR + \sigma_9 N\_ANALYSTS + \sigma_{10} REG + \varepsilon$$

	Upgrades				Downgrades			
	Candidates	**Strength**	**Ability**	**Power**	**Candidates**	**Strength**	**Ability**	**Power**
Intercept	4.3393 ***	4.2684 ***	4.6807 ***	4.2723 ***	11.0048 ***	10.8388 ***	11.9659 ***	10.8667 ***
POLITICAL	-0.8663 ***	-1.0715 ***	-0.5104 ***	-0.9549 ***	-1.4698 ***	-1.8089 ***	-1.1504 ***	-1.5159 ***
PMAFE	0.4793 ***	0.4657 ***	0.5051 ***	0.4712 ***	0.3071 ***	0.3109 ***	0.2749 ***	0.2986 ***
*PMAFE*POLITICAL*	-0.3778 **	-0.3088 *	-0.3451 ***	-0.3523 **	-0.3105	-0.4206 *	-0.0069	-0.2536 ***
FIRMEXP	-0.0686 ***	-0.0677 ***	-0.0710 ***	-0.0683 ***	-0.1412 ***	-0.1396 ***	-0.1415 ***	-0.1417 ***
BSIZE	0.0088 ***	0.0089 ***	0.0089 ***	0.0089 ***	0.0048 ***	0.0048 ***	0.0047 ***	0.0048 ***
N_FIRMS	0.0029	0.0031	0.0024	0.0031	-0.0064	-0.0059	-0.0068	-0.0061 ***
REC_FREQ	-0.0182	-0.0189	-0.0180	-0.0181	-0.1316 ***	-0.1323 ***	-0.1350 ***	-0.1313 ***
LFR	0.0350 ***	0.0351 ***	0.0349 ***	0.0351 ***	0.0817 ***	0.0815 ***	0.0817 ***	0.0816 ***
N_ANALYSTS	-0.0592 ***	-0.0582 ***	-0.0620 ***	-0.0583 ***	-0.1027 ***	-0.1018 ***	-0.1029 ***	-0.1026 ***
REG	-0.7650 ***	-0.7546 ***	-0.7918 ***	-0.7588 ***	-2.0101 ***	-1.9945 ***	-2.0403 ***	-2.0122 ***
Adj. R^2	1.09%	1.10%	1.08%	1.10%	3.41%	3.44%	3.40%	3.41%
n	149,960	149,960	149,960	149,960	64,206	64,206	64,206	64,206

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 214,166 observations estimated over 1993 - 2011.

Upgrades (downgrades) are recommendations that are higher (lower) than the previous recommendation for analyst i for firm j during year t. The 4 columns in this table use 4 different proxies for political connections (POLITICAL): Candidates, Strength, Ability, and Power. POLITICAL equals 1 if politically connected, 0 otherwise. See Appendix A for variable definitions. RET is the market-adjusted return to recommendation k made by analyst i for firm j. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL is the number of supported candidates by firm j in year t. PMAFE is the difference between the absolute forecast error for analyst i for firm j at time t scaled by the mean absolute forecast error for firm j at time t. FIRMEXP is the number of years through year t for which analyst i supplied forecasts for firm j. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst i works for during year t. N_FIRMS is the number of firms for which analyst i issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst i issues for firm j during year t. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast k divided by the cumulative number of days by which the subsequent two forecasts follow forecast k. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm j during year t. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

Table 10
The Effect of Stock Recommendation Initiations versus Non-Initiations

$$RET = \rho_0 + \rho_1 POLITICAL + \rho_2 PMAFE + \rho_3 PMAFE*POLITICAL + \rho_4 FIRMEXP + \rho_5 BSIZE + \rho_6 N\_FIRMS + \rho_7 REC\_FREQ + \rho_8 LFR + \rho_9 N\_ANALYSTS + \rho_{10} REG + \varepsilon$$

	Initiations				Non-Initiations			
	Candidates	**Strength**	**Ability**	**Power**	**Candidates**	**Strength**	**Ability**	**Power**
Intercept	3.5924 ***	3.5394 ***	3.8362 ***	3.5338 ***	7.8029 ***	7.6602 ***	8.5272 ***	7.6676 ***
POLITICAL	-0.9401 ***	-1.0571 ***	-0.3661 **	-1.0098 ***	-1.0995 ***	-1.3720 ***	-0.8407 ***	-1.2217 ***
PMAFE	0.2394 ***	0.2288 ***	0.2648 ***	0.2342 ***	0.4053 ***	0.3986 ***	0.4281 ***	0.4005 ***
*PMAFE*POLITICAL*	-0.1183	0.0164	-0.2298 *	-0.0621	-0.4831 ***	-0.5013 ***	-0.3384 ***	-0.4862 ***
FIRMEXP	0.0834 **	0.0859 **	0.0649	0.0865 **	-0.1062 ***	-0.1049 ***	-0.1064 ***	-0.1058 ***
BSIZE	0.0095 ***	0.0095 ***	0.0095 ***	0.0095 ***	0.0053 ***	0.0053 ***	0.0052 ***	0.0053 ***
N_FIRMS	0.0044	0.0046	0.0040	0.0046	-0.0027	-0.0025	-0.0029	-0.0026
REC_FREQ	-0.1476 **	-0.1482 **	-0.1436 **	-0.1482 **	-0.0477 ***	-0.0484 ***	-0.0503 ***	-0.0472 ***
LFR	0.0400 ***	0.0400 ***	0.0398 ***	0.0400 ***	0.0602 ***	0.0602 ***	0.0602 ***	0.0602 ***
N_ANALYSTS	-0.0178 ***	-0.0177 ***	-0.0234 ***	-0.0171 ***	-0.1021 ***	-0.1010 ***	-0.1027 ***	-0.1011 ***
REG	-0.5391 ***	-0.5333 ***	-0.5730 ***	-0.5342 ***	-1.5807 ***	-1.5690 ***	-1.6060 ***	-1.5766 ***
Adj. R^2	0.82%	0.82%	1.06%	1.08%	2.23%	2.36%	2.32%	2.35%
n	94,197	94,197	94,197	94,197	167,098	167,098	167,098	167,098

*, **, *** indicate significance at the 10%, 5%, and 1% levels. The t-statistics are based on standard errors clustered by analyst.There are 261,295 observations estimated over 1993 - 2011.

Initiations are defined as the first recommendation issued by analyst *i* in the I/B/E/S database. All other recommendations are defined as non-initiations. The 4 columns in this table use 4 different proxies for political connections (POLITICAL): Candidates, Strength, Ability, and Power. POLITICAL equals 1 if politically connected, 0 otherwise. See Appendix A for variable definitions. RET is the market-adjusted return to recommendation *k* made by analyst *i* for firm *j*. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock. POLITICAL is the number of supported candidates by firm *j* in year *t*. PMAFE is the difference between the absolute forecast error for analyst *i* for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*. FIRMEXP is the number of years through year *t* for which analyst *i* supplied forecasts for firm *j*. BSIZE is the logarithm of the number of analysts employed by the brokerage that analyst *i* works for during year *t*. N_FIRMS is the number of firms for which analyst *i* issues annual forecasts during the year in which the recommendation is made. REC_FREQ is the number of recommendations analyst *i* issues for firm *j* during year *t*. LFR, leader-follower ratio, is the cumulative number of days by which the preceding two forecasts lead forecast *k* divided by the cumulative number of days by which the subsequent two forecasts follow forecast *k*. N_ANALYSTS is the number of analysts who issue forecasts and recommendations for firm *j* during year *t*. REG equals 1 if firm is in financial services industry (one-digit SIC code 6) or utilities industry (two-digit SIC code 49), and 0 otherwise.

connected firms does not increase analyst efficiency in translating forecast accuracy into informative recommendations since non-initiation recommendations appear to be driving the negative association.

9. SUMMARY AND CONCLUSION

This study examines how financial analysts use information on political connections in their earnings forecasts and stock recommendations. First, I analyze whether analysts' stock recommendations are more or less informative when the firms they cover have political connections. Second, I investigate whether analysts' earnings forecast accuracy is more or less consistent with recommendation informativeness for politically connected firms.

I find strong evidence that analysts' stock recommendations are significantly less informative when the firms they follow have political connections. I find that the negative relation between recommendation informativeness and political connections holds for both All-Star and non-All-Star analysts, upgrade and downgrade recommendations, as well as initiation and non-initiation recommendations. I also show that analysts' earnings forecast accuracy is less consistent with stock recommendation informativeness for politically connected firms. However, the negative relation between earnings forecast accuracy and recommendation informativeness for politically connected firms appears to be driven by non-All-Star analysts, upgrade recommendations, and non-initiation recommendations. This study informs the literature on analyst forecasting by documenting how political connections influence the manner in which analysts map their earnings forecasts into stock recommendations. I also show how analysts use an important source of nonfinancial information, namely political connections, in their earnings forecasts and stock recommendations. Furthermore, I contribute to the political connections literature by showing that one channel through which political connections affect firm valuation is through the earnings forecasts and stock recommendations of financial analysts.

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APPENDIX A
Variable Definitions

POLITICAL^{Candidates}	$\sum_{j=1}^{J} Candidates_{jt}$ $Candidates_{jt}$ is equal to one if the firm has contributed to candidate *j* in year *t*. *POLITICAL*^{Candidates} equals 1 if greater than industry-year mean, and 0 otherwise.
POLITICAL^{Strength}	$\sum_{j=1}^{J} Candidates_{jt} \times I_{jt} \times \frac{NCV_{jt}}{NOV_{jt}} \times rellength_{jt}$ $Candidates_{jt}$ is equal to one if the firm has contributed to candidate *j* in year *t*, and 0 otherwise. I_{jt} is equal to one if the candidate is incumbent at time *t*, and 0 otherwise. NCV_{jt} (NOV_{jt}) is the number of votes that candidate *j*'s party (opposing party) holds in office at time *t*, and $rellength_{jt}$ is the number of continuous months of the firm-candidate relationship. *POLITICAL*^{Strength} equals 1 if greater than industry-year mean, and 0 otherwise.
POLITICAL^{Ability}	$\sum_{j=1}^{J} HomeCandidate_{jt} \times I_{jt} \times \frac{NCV_{jt}}{NOV_{jt}}$ $HomeCandidate_{jt}$ is equal to one if the firm has contributed to candidate *j* in year *t* and the firm is headquartered in the same state in which the candidate is running for office, and 0 otherwise. I_{jt} is equal to one if the candidate is incumbent at time *t*, and 0 otherwise. NCV_{jt} (NOV_{jt}) is the number of votes that candidate *j*'s party (opposing party) holds in office at time *t*. *POLITICAL*^{Ability} equals 1 if greater than industry-year mean, and 0 otherwise.
POLITICAL^{Power}	$\sum_{j=1}^{J} Candidates_{jt} \times I_{jt} \times \frac{NCV_{jt}}{NOV_{jt}} \times \left[\sum_{m=1}^{M} \frac{Rank_{mt}}{Median\ Rank_{mt}}\right]_j$ $Candidates_{jt}$ is equal to one if the firm has contributed to candidate *j* in year *t*, and 0 otherwise. I_{jt} is equal to one if the candidate is incumbent at time *t*, and 0 otherwise. NCV_{jt} (NOV_{jt}) is the number of votes that candidate *j*'s party (opposing party) holds in office at time *t*. $Rank_{mt}$ is the reciprocal of candidate $_j$'s rank on committee $_m$ (where rank =1 for the most important member, rank = 2 for the next important member, etc.). $Median\ Rank_{mt}$ is the median number of members on committee *m*. *POLITICAL*^{Power} equals 1 if greater than industry-year mean, and 0 otherwise.

RET	The market-adjusted return to recommendation *k* made by analyst *i* for firm *j*. The buy-and-hold return is computed from the day before the recommendation date until the earlier of 30 days or 2 days before the recommendation is revised or reiterated. For buy (hold and sell) recommendations, $1 is invested (shorted) in the recommended stock.
PMAFE	The difference between the absolute forecast error for analyst *i* for firm *j* at time *t* scaled by the mean absolute forecast error for firm *j* at time *t*.
FIRMEXP	The number of years through year *t* for which analyst *i* supplied forecasts for firm *j*.
BSIZE	The logarithm of the number of analysts employed by the brokerage firm that analyst *i* works for during year *t*.
N_FIRMS	The number of firms for which analyst *i* issues annual forecasts during the year in which the recommendation is made.
REC_FREQ	The number of recommendations analyst *i* issues for firm *j* during year *t*.
LFR	The leader-follower ratio is the cumulative number of days by which the preceding two forecasts lead forecast *k* divided by the cumulative number of days by which the subsequent two forecasts follow forecast *k*.
N_ANALYSTS	The number of analysts who issue forecasts and stock recommendations for firm *j* during year *t*
REG	Equals 1 if the firm operates in the financial services industry (one-digit SIC code 6) or in the utilities industry (two-digit SIC code 49), and 0 otherwise.
ACTIVE	Equals 1 if the firm has a registered political action committee, 0 otherwise.
SIZE	Natural log of price times shares outstanding (prcc_f * csho).
SALES	Natural log of sales.
EMPLOYEES	Natural log of number of employees in millions (emp).
BUS_SEG	The number of business segments.
GEO_SEG	The number of geographic segments.
BM	Book-to-market ratio is stockholders' book equity divided by market value [ceq/(prcc_f*csho)]
LEV	The sum of long-term debt and debt in current liabilities, divided by total assets [(dltt + dlc)/at].
CFO	Operating cash flow divided by total assets [(oancf - xidoc)/at].
MARKET_SHARE	Sales divided by total industry sales.
HERF	Herfindahl index of industry concentration computed with net sales.
INDUSTRY_ACTIVE	Number of firms in a firm's industry with an established political action committee.

APPENDIX B

First-Stage Probit Model of Firm's Decision to be Politically Active

$$ACTIVE = \lambda_0 + \lambda_1 SIZE + \lambda_2 SALES + \lambda_3 EMPLOYEES + \lambda_4 BUS\_SEG + \lambda_5 GEO\_SEG + \lambda_6 BM + \lambda_7 LEV + \lambda_8 CFO + \lambda_9 MARKET\_SHARE + \lambda_{10} HERF + \lambda_{11} REG + \lambda_{12} INDUSTRY\_ACTIVE + \varepsilon$$

	Coefficient	Std. Error	*p*-value
Intercept	-6.9422 ***	0.0982	<.0001
SIZE	0.1159 ***	0.0123	<.0001
SALES	0.4754 ***	0.0200	<.0001
EMPLOYEES	0.1928 ***	0.0164	<.0001
BUS_SEG	0.0364 ***	0.0068	<.0001
GEO_SEG	-0.0726 ***	0.0078	<.0001
BM	0.0000	0.0000	0.9115
LEV	0.0139 ***	0.0042	0.0008
CFO	0.2128 *	0.1113	0.0558
MARKET_SHARE	0.1269	0.3593	0.7240
HERF	2.1618 ***	0.2482	<.0001
REG	0.4200 ***	0.0462	<.0001
INDUSTRY_ACTIVE	0.0174 ***	0.0012	<.0001
R^2	36.34%		

There are 92,375 firm-year observations estimated over 1993 - 2011. ACTIVE equals 1 if the firm has a registered political action committee, 0 otherwise. SIZE is the natural logarithm of price times shares outstanding (prcc_f * csho). SALES is the natural logarithm of sales. EMPLOYEES is the natural logarithm of the number of employees in millions (emp). BUS_SEG is the number of business segments. GEO_SEG is the number of geographic segments. BM, book-to-market, is stockholders' book equity divided by market value [ceq/(prcc_f*csho)]. LEV is the sum of long-term debt and debt in current liabilities, divided by total assets [(dltt + dlc)/at]. CFO is operating cash flow divided by total assets [(oancf - xidoc)/at]. MARKET_SHARE is sales divided by total industry sales. HERF is the Herfindahl index of industry concentration computed with net sales. REG equals 1 if the firm operates in the financial services industry (one-digit SIC code 6) or in the utilities industry (two-digit SIC code 49), and 0 otherwise. INDUSTRY_ACTIVE is the number of firms in a firm's industry with an established political action committee. All continuous variables are winsorized at 1 and 99 percent to mitigate outliers.

VITA

Elio Alfonso was born in Meriden, Connecticut. He attended high school at Fayetteville-Manlius High School in Manlius, New York. He graduated with a Bachelor in Business Administration with a major in Finance from Florida International University in 2001. He also graduated with Master in Accounting from Nova Southeastern University in 2008. He is a licensed Certified Public Accountant in the state of Florida. He has worked as a financial advisor, accounting analyst, and auditor for a total of eight years. His teaching interests include Financial Accounting, Intermediate Accounting I and Intermediate Accounting II. His research interests include, but are not limited to, financial analysts' earnings forecasts and stock recommendations, income classification shifting, cash flow restatements, direct cash flow disclosures, earnings management, corporate social responsibility, and political connections.