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Essays in Empirical Corporate Finance

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Essays in Empirical Corporate Finance

by

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ABSTRACT OF THE DISSERTATION

by

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This dissertation presents three essays in empirical corporate finance. In the first two essays, I examine the effect of analyst coverage network on US firms' corporate decisions and stock return comovement in emerging markets. The third essay discusses the importance of performance pay and CEO functional background in explaining firm performance in the short- and long-run.

In the first chapter, which is a joint work with Armando Gomes, Radha Gopalan and Mark Leary, we show that sell-side analysts play an important role in propagating corporate financial policy choices, such as leverage and equity issuance decisions across firms. Using exogenous characteristics of analyst network peers as well as the "friends-of-friends" approach from the network effects literature to identify peer effects, we find that exogenous changes to financial policies of firms covered by an analyst leads other firms covered by the same analyst to implement similar policy choices. We find that a one standard deviation increase in peer firm average leverage is associated with a 0.35 standard deviation increase in a firm's leverage, and a one standard deviation increase in the frequency of peers' equity issuance leads to a 29.6% increase in the likelihood of issuing equity. We show evidence that these analyst network peer effects are distinct from industry peer effects and are more pronounced among peers connected by analysts that are more experienced and from more influential brokerage houses.

In the second chapter, I provide evidence that sell-side analyst coverage networks (ACN)

play an important role explaining the comovement and excess comovement of stock return across Latin American countries. The study tests empirically the *Coverage-Specific Information Spillover Hypothesis* (Muslu et al. 2014) of the information generated and disseminated by analysts. Using the pair model for the sample period 2000-2014 and more than 75,000 firm-pair-year observations, I provide evidence that firms connected by analysts in common have higher comovement and excess comovement. In addition, I perform cross-sectional tests to show that firms easily traded by foreign investors are more affected by shared coverage. Also, I find that an important source of across-country excess comovement is the shared coverage by international analysts. Then, I test whether firms followed by the same brokerage houses also face higher stock return comovement. The results suggest that both analysts and brokerage houses matter, but I find the strongest effects associated with the ACN. Finally, I exploit exogenous changes in the ACN around the MSCI Latin American Index reviews to address endogeneity concerns about the effect of ACN on commonalities.

In my last chapter, I use a comprehensive dataset based on the accounting performance goals employed by firms to provide evidence that boards of directors design executive compensation to cater to investor demand. I show that they tie the compensation to accounting metrics (performance pay) preferred by investors in order to improve firm performance and boost the current stock price. Moreover, the results suggest that both performance pay and functional background are important determinants of firm performance. However, functional background has a long lasting impact as compared to performance pay. In addition, the study shows that the effectiveness of linking CEO compensation to accounting metrics depends on CEO tenure. Performance pay is more important for recently appointed CEOs and its effect is also important to improve long-term performance. Finally, I provide evidence that firms obtain better performance when boards of directors hire new leaders and design compensation plans consistent with the functional background of the incoming CEOs.

Chapter 1

Analyst Coverage Network and Corporate Financial Policies

1.1 Introduction

Sell-side analysts are important players in financial markets. Their role in acquiring, analyzing, and disseminating information for investors has been much studied (Frankel et al. (2006), Kadan et al. (2012); Muslu et al. (2014); Chang et al. (2006); Piotroski and Roulstone (2004)). In addition to their role as information intermediaries between firms and investors, there is growing evidence that analysts may also influence the policies of the firms they cover (Kaustia and Rantala (2015); Degeorge et al. (2013); Becher et al. (2015)). Analysts can communicate their preferred financial policy to management through conference calls, analyst reports, etc. Management in turn will be willing to adopt those policies either if they are perceived to be value enhancing or if management wishes to cater to the analyst (Degeorge et al. (2013)). An indirect channel of analyst influence is when managers, in their effort to meet analyst forecasts, alter firm financial and investment policies (Bhojraj et al. (2009); Gunny (2010); Hribar et al. (2006)).[1] In this paper, we argue that analysts may affect corporate financial policies by transmitting information across portfolio firms.

Analysts cover a portfolio of firms often spread across multiple industries. Apart from regularly communicating with the firms, analysts also employ common models to value the

[1]Managers sometimes engage in real activities manipulation. For instance, reducing R&D when actual earnings may be lower than the analyst consensus.

firms and benchmark them with one another. During the course of their communication and valuation, analysts may come across information that can effectively be transferred from one firm to another. Such information can be about the state of financial markets, growth opportunities, or about the suitability of a particular financial policy. If analysts communicate such intelligence to management and if the firms follow the analysts' recommendation, then we expect financial policies to be correlated among firms with common analysts. Note that although the policies of peer firms may be public knowledge, we believe analysts may still play an important role in communicating the suitability of the policy for a particular firm. We use the latest identification techniques from the social networks literature to document the causal effect of analyst peer firm financial policies on a firm's financial policy.

We identify "exogenous" changes to financial policies of firms covered by an analyst and test to see if other firms covered by the same analyst experience similar changes in policy. We focus on financial policies such as leverage, debt issuance, and equity issuance. We classify all firms that share a common analyst with a firm as its "analyst peers" and relate the firm's financial policy to the weighted average financial policy of its analyst peers. We use the number of common analysts between the firm and its peer firms as the weights. This methodology gives rise to a network, which we refer to as the analyst coverage network–i.e., the graph where the firms are the nodes and the weighted edges between two firms are the number of common analysts between the firms.

We use empirical methods from the social networks literature to identify peer effects in the analyst coverage network. As discussed by Manski (1993), a positive association between a firm's financial policy and that of its peers can arise from one of three sources. First, there can be one or more unobserved common characteristic between the firm and its peers. This is what Manski (1993) calls "correlated effects". For example, firms in the same analyst network are likely to operate in similar product markets and thus share common characteristics. These common characteristics can result in the firms choosing similar financial policies. To the extent analysts have "exogenous" preferences about financial policies and directly influence their portfolio firms to implement those policies, it can also generate correlated effects.

Second, firms may change their financial policy in response to changes in some peer firm characteristic. For example if a peer firm gets a new investment opportunity, a firm may respond by possibly changing its investment and financial policy. This is referred to as “exogenous peer effects”. The word exogenous refers to the change in the “exogenous” characteristic driving the change in financial policy. Finally, changes to peer firm financial policy may causally influence a firm’s financial policy. This is referred to as “endogenous peer effect” and is the one that we wish to document. Our objective is to establish the presence of endogenous peer effects among firms covered by common analysts. Distinguishing between exogenous and endogenous effects is important since, for example, there are policy interventions such as targeted industry tax subsidies for debt financing, which may influence the financial policy of peers while leaving their fundamentals unchanged. These policies may still generate multiplier effects through endogenous peer effects (Glaeser et al. (2003)).

We follow two methodologies to establish the existence of endogenous peer effects. First, to isolate correlated effects from endogenous and exogenous peer effects (we refer to these as social effects from now), we follow Leary and Roberts (2014) and use idiosyncratic equity return shocks as an exogenous source of variation in peer firm financial policy (and possibly characteristics). A large prior literature in finance shows that firms change their leverage, debt and equity issuance decision in response to changes to their stock price (Baker and Wurgler (2002); Leary and Roberts (2005)). To the extent we are able to isolate idiosyncratic shocks to peer firm’s equity value, the shocks are unlikely to be correlated with the characteristics of the firm in question and thus any peer effects we document are unlikely to include correlated effects. Note that idiosyncratic changes to peer firms’ stock price can influence a firm’s policies either because the return shocks affect the peers’ financial policies or because the return shocks reflect changes in one or more of peers’ characteristics.[2] To this extent this methodology will not allow us to distinguish between endogenous and

[2] Or perhaps both. For example, a shock to a peer firm’s investment opportunities that generates a positive return shock may affect the peer’s investment behavior and also elicit an equity issuance to fund the investment.

exogenous peer effects.

To distinguish endogenous peer effects from exogenous peer effects we exploit the fact that analyst networks partially overlap. Thus we can observe firm triads i, j and k, such that firms i & j and firms j & k have common analysts while firms i & k do not have any. This is a key property of the analyst coverage network that allows for identification.[3] Following the "friends of friends" approach outlined in Bramoullé et al. (2009) and Goldsmith-Pinkham and Imbens (2013), we use the exogenous characteristic of firm k, namely idiosyncratic equity shock as an instrument for the financial policy of firm j to document its influence on firm i's financial policy. The exclusion restriction for this approach is that firm k's equity shock should influence firm i's financial policy only through its influence on firm j's financial policy and not otherwise. Given our interest in controlling for exogenous peer effects another way to state this is, firm k's equity shock should not be correlated with either firm j or firm i's characteristic. To the extent we are able to isolate "idiosyncratic shocks" to equity values, this assumption is reasonable. It follows the same logic as outlined in Leary and Roberts (2014).

We begin by documenting a positive association between a firm's financial policy and that of its analyst peers. We find that this association extends to all the outcome variables we model and to analyst peers not from the same industry. Next we implement reduced-form regressions that documents a robust association between a firm's financial policy and the idiosyncratic return shocks of its analyst network peers. We find that this association is robust to controlling for the financial policies and characteristics of the firm's industry peers, as well as the characteristics of the firm and its analyst peers. The positive association exists for leverage, changes in leverage, equity issues and share repurchases. Thus our results are consistent with the existence of "social effects" for leverage, equity issues and share repurchases.

Next, we use the idiosyncratic shock to peer firms' stock prices (*Equity shock*) as an

[3] Note that this is in contrast to, for example, peer effects arising due to industry membership. If firms i & j and j & k belong to the same industry, then i & k must also belong to the same industry.

instrument for peer firm financial policies in a two-stage least squares (2SLS) specification and find that we obtain consistent results. To the extent this 2SLS does not isolate endogenous peer effects, we will not be able to interpret the estimates as the causal effect of peer firm financial policy on a firm's financial policy.

We take several steps to establish that our results capture the role of analyst networks and not other common factors such as industry. First, as mentioned before, in all our tests, we control for industry average policies, either directly or through industry average return shocks. Second, we find similar results when we focus on the firms in the analyst network that are not from the same industry as the firm in question. Third, we estimate a placebo test in which we define pseudo peer groups as firms in the same industry as a firm's direct analyst peers but that do not have a common analyst with the firm in question. We find no relation between the return shocks of the pseudo peers and the firm's financial policy.

We further document cross-sectional variation in our estimated effects that are consistent with information propagating through the analyst network. First, we find that smaller and less successful firms are influenced by the larger and more successful ("leader") firms in their analyst network, but not vice versa. Second, we test to see if analysts that are expected to be more influential are more effective at transmitting information across firms. Consistent with this idea, we find stronger peer effects among firms connected by more experienced analysts and by analysts from brokerage houses with more "all-star" rated analysts.

Finally using the friends of friend methodology from the social network literature, we document the presence of endogenous peer effects among firms covered by analysts. Using the equity shock of indirect peer firms as an instrument for peer firm financial policies, we document an economically significant endogenous peer effect. A one standard deviation increase in peer firm average leverage is associated with a 0.35 standard deviation increase in a firm's leverage. Peer effects are also present in a firm's decision to issue equity. A one standard deviation increase in peer firm's average equity issuance leads to a 29.6% increase in the likelihood of a firm issuing equity. Overall, after controlling for the endogeneity in the network formation we find that peer firms in the same analyst coverage network affect each other.

We make a number of important contributions. First, we document the important role of analysts in propagating financial policies across firms. An important question that we do not answer is whether such propagation is efficient or results in inefficient mimicking. Future research should explore this important question. Our second contribution is methodological. We are the first in the finance literature to use the "friends of friends" approach to document the existence of endogenous peer effects. This approach can be productively used to document endogenous peer effects in other networks that partially overlap such as board networks and supply chain networks.

The rest of the paper is organized as follows. Section 1.2 discusses the related literature. Section 1.3 discusses our data and empirical methodology. Section 1.4 provides the summary statistics and section 1.5 discusses the empirical evidence. Finally, section 1.6 concludes. Definitions of empirical variables are in Appendix A.

1.2 Literature Review

This paper is related to two main streams of literature. The first is related to the role of analysts in the financial markets and the second explores the effect of social networks in corporate finance. Our paper contributes to the literature by showing that analysts are an important mechanism underlying peer effects in financial policy and that analysts influence the way firms interact with one another.

A large literature studies the role of analysts as information intermediaries between firms and outside investors. Prior studies indicate that analysts acquire, analyze, and disseminate useful information to investors.[4] Evidence from Kelly and Ljungqvist (2012) suggests this information production of analysts is effective in reducing information asymmetry in financial markets. Additionally, a number of recent studies have shown evidence that analysts can impact the decisions of the firms they follow. For example, Chen et al. (2015)

[4]Examples include Womack (1996); Piotroski and Roulstone (2004); Frankel et al. (2006); Kadan et al. (2012); Muslu et al. (2014), among others.

show that the monitoring activities of analysts help align managerial behavior with investor interests. Other studies show that analysts' information production impacts firms' cost of capital (Derrien and Kecskés (2013b); Fracassi et al. (2014)), security issuance decisions (Chang et al. (2006)) and merger completion probability (Becher et al. (2015)). Degeorge et al. (2013) show evidence that analysts have preferred financial policies, which they influence firms to follow. Relative to these earlier studies, our study highlights a previously unexplored role of analysts that also impacts firm policies, namely that they facilitate peer effects by transmitting information among firms.

The second stream of the literature explores how peer effects, or the interaction among agents, can affect outcomes. There is a vast economics literature along this line and a growing literature in corporate finance analyzing the role of social networks on firm financial policy decisions. Shue (2013) shows that executive compensation and acquisitions strategies are significantly more similar among graduates from the same (randomly assigned) MBA section than among graduates from different sections. Fracassi (2016) studies the impact of social ties among managers from past employment and education and their corporate policy decisions. He finds that more connections two companies share with each other, more similar their capital investments are. Cai and Sevilir (2012) show that performance in M&A transaction of acquirers is better when the acquirer and the target share a common director. In the asset management area, Cohen et al. (2008) focus on the education network between mutual fund managers and corporate board members. They find that mutual fund managers invest more and perform significantly better on stock holdings for which the board members went to school together with the mutual fund managers. Matvos and Ostrovsky (2010) document peer effects among mutual fund managers in proxy voting.

Our paper differs from these earlier ones in our focus on the role of analyst networks as a mechanism behind corporate peer effects. Kaustia and Rantala (2013, 2015) also examine peer effects within the context of analyst coverage networks. However, their focus is on stock split decisions and they use analyst networks to identify groups of related firms rather than studying the role of analysts in transmitting information among firms.

Our paper also differs methodologically from earlier studies of peer effects in corporate finance. We use recent econometric methodologies developed to identify peer effects (endogenous versus exogenous effects) in social networks. Our main model is an extended version of the Manski-type linear-in-means model studied in Goldsmith-Pinkham and Imbens (2013) and Bramoullé et al. (2009) (see also the survey by Blume et al. (2010)). A key property of the analyst coverage network that allows for identification of peer effects is that there exist many firms that are not directly connected to a firm through a common analyst, but that do share a common analyst with other firms in the analyst network. We refer to these as indirect analyst peers. We use the characteristics of the indirect analyst peers, including idiosyncratic equity shocks to indirect peers, as instruments for the financial policy of firm's direct peers to estimate peer effects in financial policy.

1.3 Data and Empirical Methodology

1.3.1 Data and Key Variables

We obtain our data from standard sources: financial information from Compustat, stock price information from CRSP, and analyst coverage information from IBES. From the overall CRSP-Compustat merged sample, we exclude financial firms (SIC codes between 6000 and 6999), utilities (SIC codes between 4900 and 4949) and government companies (SIC codes greater than or equal to 9000). We then match the CRSP-Compustat sample to IBES and identify all firms that are connected to at least one other firm in the sample through a common analyst. We identify an analyst as following a firm in a fiscal year if she makes at least one earnings forecast during the year and the forecast is made at most six months before the end of the fiscal period and at least three months after the end of the fiscal period. We also require the analyst to follow the pair of firms for at least two years in the entire sample for us to consider them to be connected through the analyst. Our sample spans the period 1993-2013 and includes 37,745 firm-year observations.

We begin by documenting the extent to which financial policies of analyst peers are associated with a firm's financial policy. We do that by estimating the following regression:

$$y_{ijt} = \alpha + \beta_1 y^{ACN}_{-it} + \beta_2 y^{IND}_{-ijt} + \gamma_1^{'} X^{ACN}_{-it-1} + \gamma_2^{'} X^{IND}_{-ijt-1} + \gamma_3^{'} X_{ijt-1} + \delta^{'} u_i + \phi^{'} v_t + \epsilon_{ijt} \quad (1.1)$$

where the indices i, j and t refer to firm, industry and year respectively. The dependent variables that we model are, *Market leverage*, *Net debt issuance (1%)*, *Net equity issuance (1%)* and *Gross equity issuance (1%)*. Specifically, we employ the level and change in leverage. When we consider debt and equity issuances we use an indicator equal to one if the firm issues debt (equity) in excess of 1% of total assets, and zero otherwise.[5] All variables we use in our analysis are defined in the Appendix A. X_{ijt-1} is the set of firm-specific controls. Following Leary and Roberts (2014), we include lagged (one period) values of *Log(Sales)*, *Market-to-book*, *Tangibility* and *Profitability* as our controls. y^{ACN}_{-it} represents the weighted average value of the outcome variable for all the firms that are connected to firm i through common analysts (analyst network from now). The weights for each firm l in the analyst network represents the number of common analysts between firm l and firm i. Specifically:

$$y^{ACN}_{-it} = \frac{\sum^{I}{}_{(i \neq l)} n_{ilt} y_{lt}}{\sum^{I}{}_{(i \neq l)} n_{ilt}} \quad (1.2)$$

where n_{ilt} represents the number of common analysts between firm i and firm l. Note that in calculating y^{ACN}_{-it} we use the financial policies of peer firms in the current year along with the current network structure. We use a weighted average instead of a simple average to give more weight to peer firms with more analysts in common with a firm. Such peers may have a stronger influence on a firm's financial policy because there is a greater likelihood that one or more analysts will transmit information across the firms. Our coefficient of interest is β_1. We also include a set of weighted average peer firm characteristics (X^{ACN}_{-it-1}) as controls. These are the same set of characteristics included in X_{ijt-1} and discussed above. In calculating X^{ACN}_{-it-1}, we use the current network structure along with lagged peer

[5]In all the regressions we use the 1% threshold for the gross and net equity (debt) issuances to define the indicator variable. We explicitly identify the cases in which we use a different threshold.

firm characteristics.

To distinguish the effect of analyst network peers from that of industry peers (Leary and Roberts (2014)), we also control for the average value of the outcome variable for all other firms in the same industry (based on three-digit SIC code), y^{IND}_{-ijt} (excluding the firm i) and their average characteristics, X^{IND}_{-ijt-1}, as additional controls.[6] In all the regressions, except for those with changes in *Leverage* as the outcome variable, we include firm- and year-fixed effects. For the regressions with change in leverage as the outcome variable, we include industry- and year-fixed effects. The standard errors we estimate are robust to heteroskedasticity and clustered at the firm-level.

As shown in Manski (1993), a significant β_1 can arise from one of three sources. First, it can reflect the fact that there are some unobserved similarities among firms in the same analyst network (correlated effects). These similarities may result in the firms choosing similar financial policies. Alternatively it can arise from firms responding to either the behavior (endogenous peer effects) or characteristics (exogenous peer effects) of the peer firms. To control for correlated effects, following Leary and Roberts (2014), we use idiosyncratic shocks to the value of the peer firm's equity as an instrument for their financial policy (or characteristic). We define expected returns based on a one-factor market model augmented to include the excess return on the analyst network portfolio. We use the equally-weighted portfolio returns of all firms that share a common analyst with a firm to calculate the excess returns. While the excess return on the analyst network firms does not necessarily represent a priced risk factor, we include it to absorb any common shocks that may affect firms in the same analyst network.[7] For example, Muslu et al. (2014) and Israelsen (2014) show that shared coverage explains comovement and excess comovement between pairs of stock with common analysts. Thus, we model the firm's stock return as:

[6] We also create an alternative measure of industry average outcomes that includes only firms that are in the same industry as firm i, but they are not in the same analyst network as firm i. In other words, we exclude the set of firms that overlap across the analyst coverage network and industry of firm i.

[7] Leary and Roberts (2014) show evidence that this strategy produces idiosyncratic return estimates that are uncorrelated, both serially and cross-sectionally, within networks.

$$r_{it} = \alpha_{it} + \beta_{it}^{M}(rm_t - rf_t) + \beta_{it}^{ACN}(\bar{r}_{-it}^{ACN} - rf_t) + \eta_{it}$$

where the subscript t refers to time in months, rm_t and rf_t are the monthly return on the market and risk free asset respectively, $\bar{r}_{-it}^{ACN}$ is the equally weighted average return of all firms in the analyst network of firm i. We estimate this regression individually for each firm-year using a five year rolling window.[8] We then calculate, *Equity shock* for firm i in year t as the difference between the return on the firm's stock in year t and the predicted return based on the market and peer portfolio excess returns during the year and the loadings estimated using the data from the prior five years. We require firms to have at least 24 months of historical data to estimate the above model. *Equity shock* represents the idiosyncratic shock to a firm's stock return. We then calculate the weighted average equity shock for the analyst network, $Equity\ shock_{-it}^{ACN}$, using the number of common analysts as the weights and the industry average equity shock, $Equity\ shock_{-ijt}^{IND}$, as the simple average equity shock for all firms in the same industry as firm i.

We use $Equity\ shock_{-it}^{ACN}$ as an instrument for y_{-it}^{ACN} and employ a reduced form model and 2SLS to estimate its effect on firm i's financial policy after controlling for industry corporate policy and industry characteristics. To the extent $Equity\ shock_{-it}^{ACN}$ captures idiosyncratic shocks to the stock price and consequently leverage of analyst peer firms, it is unlikely to be correlated with firm i's characteristics. To this extent the reduced form model and the 2SLS will isolate the social effects and exclude correlated effects. The specific identifying assumptions that we make for this are the following. First, for instrument relevance we assume that $Equity\ shock_{-it}^{ACN}$ is correlated with the peer firm's financial policy either directly or indirectly through one or more characteristic. A large prior literature documents the important effect stock prices can have on firm financial policies (Baker and Wurgler (2002); Leary and Roberts (2005)) and stock price changes often reflect changes in firm characteristics such as investment opportunities, expected profitability or risk, which in turn have been shown to be important determinants of firm financial policies. This ensures

[8] In each year we calculate monthly peer returns using the firm's analyst network in that year. In order to calculate $\bar{r}_{it}^{ACN}$, we require that a firm has at least one peer firm with valid returns during the time period in which we estimate the loadings.

the relevance assumption is satisfied in our setting. Furthermore as we make clear later, the instrument is strongly correlated with firm financial policies in the first stage with a high F-statistic. The second assumption we make to isolate social effects is that $\textit{Equity shock}_{-it}^{ACN}$ is uncorrelated with firm i's characteristics but through its effect on firm i's policies (or characteristics). To the extent our procedure for defining $\textit{Equity shock}_{-it}^{ACN}$ isolates truly idiosyncratic shocks, this assumption is likely to be valid.

Note that our tests employing $\textit{Equity shock}_{-it}^{ACN}$ as an instrument will not be able to isolate endogenous peer effects from exogenous peer effects because the idiosyncratic shock to equity values can change, or reflect changes in (some unobserved) peer firm characteristic and firms may respond to the changes to peer firm characteristic as opposed to the changes in peer firm behavior. To isolate the endogenous peer effects from exogenous peer effects, we exploit the fact that analyst networks partially overlap with each other. In other words, we can observe firm triads *i, j* and *k*, such that firms i & j and firms j & k have common analysts while firms i & k do not have any common analyst. Following the "friends-of-friends" approach outlined in Bramoullé et al. (2009), we use the characteristic of firm k (namely *Equity shock*) as an instrument for the financial policy of firm j to identify its influence on firm i's financial policy. In our subsequent discussion we refer to firm k as an indirect peer of firm i. Note that we use a slightly modified and in some senses a stricter version of the friends-of-friends approach proposed by Bramoullé et al. (2009). To identify endogenous peer effects, Bramoullé et al. (2009) only require that some of the indirect peers not be direct peers of the firm in question. If that is true then one can use the characteristics of *all* the indirect peers as instruments for peer firm behavior. In our tests we use the *Equity shock* of only *the indirect peers that are not direct peers of the firm in question* to instrument for peer firm behavior. In the example above if there was another firm m which is a peer of both firms i and j, Bramoullé et al. (2009) will allow one to use the average characteristics of both firms m and k as instruments for firm j's behavior. In our tests, we only use the characteristics of firm k as an instrument for the behavior of firm j. We exclude firm m because it is a direct peer of firm i. By construction, there are no analysts in common between firms i and k. The specific instrument we employ is the simple average *Equity* *shock*. The identifying assumptions necessary for us to isolate the endogenous peer effects are the following:

First we require that the *Equity shock* of firm k be correlated with the behavior of firm j. This will happen as long as there are some social effects. Our earlier results show that there are some social effects in our sample. Our second assumption is that firm k's equity shock should not be correlated with firm i's (and firm j's) characteristic. We believe this is a reasonable assumption because the firm and indirect peers do not have any analysts in common, and they are often not even from the same industry.[9] Furthermore *Equity shock* by construction identifies idiosyncratic shocks to a firm's equity value. Finally, since we focus on indirect peers we use a simple average of indirect peer equity shock instead of a weighted average.

1.4 Summary Statistics

Panel A of Table 1.1 provides descriptive statistics for the analysts' network. On average, a firm is connected to 41.3 other firms through common analysts. Interestingly, only 10.46 (28%) of these connections are from the same three digit-SIC code industry as the firm. The low percentage of within industry connections helps us independently estimate peer effects arising from both industry and analyst networks. Note that we exclude from our analysis firms that are not connected to any other firm through common analysts. The variable *Connected Firms* identifies the percentage of firms that are connected to at least one other firm each year in the overall CRSP-Compustat-IBES sample. We find that about 94% of the firms in the overall sample are connected to at least one other firm. Thus the unconnected firms, which we exclude, constitute only 6% of the CRSP-Compustat-IBES merged sample. The average (median) number of indirect connections–defined as the pairs i & k, such that firms i & j and firms j & k have common analysts while firms i & k do not have any– are 405.54 (373) and the 25th percentile of the number of indirect connections

[9] In a robustness test, we use only those indirect peers not in the same industry as firm i.

is 218 while the 75th percentile is 563. Most of the indirect connections are to firms in different three-digit-SIC code industries. The mean (median) number of across industry indirect connections is 385 (352)).

Our next set of variables measure the number of common analysts between two firms. We find that on average, two connected firms in our sample have 1.89 analysts in common. Surprisingly this number does not vary much in the sample. The 25th percentile of the number of common analysts is 1.1 while the 75th percentile is 2.34. We find that firms within an industry are likely to have more common analysts as compared to firms across industries. Two firms within the same industry have on average 3.11 common analysts whereas this number is only 1.54 for two firms from different industries.

Panel B reports the average value of the outcome variables we use in our analysis. We find that the average *Market leverage* in first difference (level) for the firms in our sample is 1% (21%). In comparison, the industry average *Market leverage* in first difference (level) and the peer average *Market leverage* in first difference (level) are 1% (23%) and 1% (20%) respectively. When we identify debt issuances as instances when there is a more than 1% increase in the book value of total debt relative to the book value of total assets, we find that firms issue debt during 36% of the sample period. We use two variables to identify equity issuances. Our first variable defines equity issuances as instances when the difference between cash flow from equity issues less cash flow from equity repurchases is greater than 1% of the book value of total assets. Based on this definition, firms issue equity 23% of the sample period. When we define gross equity issuances as years when the cash flow from equity issues is more than 1% of the book value of total assets, we find that equity issuances occur 36% of the firm-years.

In Panel C we provide the summary information for *Equity shock*. While the average value of *Equity shock* in our sample is close to zero at -.03, it has sufficient dispersion with a standard deviation of 0.50. Not surprisingly, *Equity shock* becomes much less dispersed when averaged over either the industry or analyst peer firms.

Finally in panel D we provide the summary information for all the control variables in our sample. The summary values are similar to those for the the full CRSP-Compustat-IBES merged sample. We winsorize all our variables of interest at the 1st and 99th percentiles.

1.5 Empirical Results

1.5.1 Baseline Regressions

In this section we discuss our empirical results. The discussion is divided into four parts. First, we document a positive association between a firm's financial policy and that of its analyst peers. We then employ *Equity shock* as an exogenous peer firm characteristic to establish the existence of social effects distinct from correlated effects. We also provide a series of robustness and placebo tests to distinguish peer effects operating through analyst networks from those operating within industries. We further perform several cross-sectional tests to investigate the hypothesis that more influential analysts are more effective in transmitting information about financial policies between firms. In our final set of tests, we employ the friends-of-friends approach to isolate endogenous peer effects from exogenous peer effects.

In Table 1.2, we provide the results of estimating equation (1) in our full sample. The outcome variable in columns (1) and (3) is *Market Leverage* in first difference and level, respectively. The positive and significant coefficient on *Industry average* highlights the positive association between a firm's leverage and average leverage of other firms in its industry (Welch (2004), Frank and Goyal (2008)). Coefficients on the firm-specific control variables are consistent with prior studies (e.g., Rajan and Zingales (1995)). From the coefficients on the industry average characteristics we find that only industry average *Profitability* is significantly related to firm leverage. Consistent with the findings in Leary and Roberts (2014), firms from more profitable industries have higher leverage.

In columns (2) and (4) we augment the model with *Peer average*, the weighted average leverage (in first difference and level) of all firms in the analyst network. We also include the weighted average characteristics of the analyst peer firms in the regressions. We find that the coefficient on *Peer average* is positive and significant. The coefficient on *Peer average* is significantly larger than that on *Industry average* and inclusion of the *Peer average* reduces the size of the coefficient on *Industry average* in first difference (level) from .461 (.405) to .253 (.286). This is consistent with analyst peer firm leverage having a large effect on a firm's leverage. Focusing on the peer firm characteristics, we find that only the coefficients on peer firm average *Log(Sales)* and *Market to book* are significant in both columns.

In columns (5)-(6) we repeat our tests with *Net debt issuance* as the dependent variable and from column (6) we find that there is a positive association between the probability of debt issuances by a firm in a year and debt issuances of analyst-connected peer firms. Here again we find that the coefficient on *Peer average* is larger than that on *Industry average*. Interestingly we find that none of the industry or analyst peer characteristics are significantly related to a firm's decision to issue debt. In columns (7) - (10) we focus on equity issuances and irrespective of our measure of equity issuance, we find that there is a positive association between equity issuances by a firm and equity issuances by analyst peer firms in the same year. The coefficients on both *Peer average* and *Industry average* are of similar magnitude. Overall our results in Table 1.2 show that firm financial policies are positively related to the financial policies of firms that are connected through common analysts. The magnitude of the association is greater than that between firm financial policy and industry average financial policies.

In Table 1.3 we differentiate between within and across industry analyst peers to see if these two groups have a similar effect on firm financial decisions. We do this by replacing *Peer average* with two variables *Peer average (within industry)* and *Peer average (across industry).* These are the weighted averages of the outcome variable for within and across industry analyst peers. We calculate the weighted average using the methodology outlined in Section 3. From columns (1)-(2) of Table 1.3 we find that the coefficients on both within and across industry peer averages are positive and significant. The coefficients are also of similar size. This indicates that both within and across industry analyst peers appear to exert a similar level of influence on firm leverage. Specifically, in unreported tests we find that the two coefficients in column (2) are not statistically distinguishable. The significant coefficient on *Peer average (across industry)* further reinforces the conclusion that the analyst network may have an independent effect on firm leverage apart from the industry effect documented in Leary and Roberts (2014). From columns (4)-(5) we find that within and across industry peer financial policies in terms of net debt issuance, net and gross equity issuance have a statistically significant association with a firm's respective financial policy. It is noteworthy that the across industry analyst peers have a larger influence on a firm's decision to issue equity as compared to within industry analyst peers.

1.5.2 Reduced Form and Structural Regression

Having established a positive association between peer firm financial policy and own firm's financial policy, we now go to our next set of tests wherein we employ *Equity Shock* as an exogenous peer firm characteristic in an effort to control for correlated effects.[10] In Table 1.4 we report the results of a reduced form estimation wherein we include *Peer Equity Shock* and *Industry Equity Shock* instead of peer and industry average financial policy and repeat our tests. We perform the reduced form analysis to provide evidence of social effects (endogenous or exogenous). However, at this point we cannot identify which one of these effects drives the results. In this table we also include *Industry Equity Shock* to highlight that the effect of *Peer Equity Shock* is robust to controlling for industry characteristics, suggesting that our peer effects results are not only due to peer firms from the same industry. We explore this issue further in subsequent tests.

From columns (1)-(2) we find that all three equity shock variables (lagged one period), *Own Equity Shock*, *Industry Equity Shock* and *Peer Equity Shock* are negatively associated with a firm's market leverage (first difference and level). To the extent that equity shock provides an exogenous shock to a firm's financial policy and characteristic, the negative and significant coefficient on *Peer Equity Shock* is consistent with the presence of social effects within the analyst network. When we model leverage (column 2), our coefficient estimates

[10]Following Leary and Roberts (2014), we use the *Equity Shock* instrument lagged one period.

on *Industry Equity Shock* and *Own Equity Shock* are similar to those reported in Leary and Roberts (2014) (see Table IV). In the change specification, however, the industry average shock becomes statistically insignificant once we control for *Peer Equity Shock*.

In column (3) our dependent variable is *Net debt issuances* and we find that while *Own Equity Shock* is negatively associated with *Net debt issuances*, both *Peer Equity Shock* and *Industry Equity Shock* are not significantly associated with *Net debt issuances*. By contrast, columns (4) - (5) indicate a strong positive association between *Peer Equity Shock* in a year and the probability of a firm making equity issues the next year. This suggests the presence of social effects in equity issuance decisions within analyst networks. Summarizing, our evidence in Table 1.4 shows that there appears to be strong social effects within analyst networks when it comes to leverage and equity issuance decision.

In Table 1.5, we use alternate thresholds to define the equity issuance dummy (1%, 3% and 5% of total assets) and also separately look at net and gross equity issuance along with equity repurchases. From columns (1)-(3) we find that our results are robust to using different thresholds to identify equity issuance. In all three columns, the coefficients on *Peer Equity Shock* and *Peer average* are positive and statistically significant. Moreover, from column (4) we also find some evidence for peer effects in equity repurchases.[11]

In Table 1.6 we provide the results of the two-staged least squares estimation that uses *Peer Equity Shock* as an instrument for the average financial policies of peer firms. In all the specifications we also include the average financial policies of firms in the same industry as an additional control. On the top of Table 1.6, we provide the coefficients on the instruments from the first stage regression. Estimating the 2SLS has advantages and disadvantages relative to the reduced form. The advantage is that it allows us to estimate the magnitude of the impact of analyst peer firm policies on firms' financial decisions. The limitation, though, is that interpreting the magnitude in this way requires us to assume that the peer firms' equity shocks influence firm i through their effect on peers' financial policies. As discussed earlier, it is possible that peers' equity shock influences firm i's policies because

[11]The lack of statistical significance in columns 5 – 6 is understandable in light of the rarity of equity repurchases in excess of 3% (5%) of assets.

it is a shock to the peers' characteristic, such as investment opportunities or competitive position. This would represent an exogenous peer effect, in which case we would be wrong to attribute the entire magnitude to endogenous peer effects i.e., the effect of peers' policies on firm i's policies.

Despite this caveat, the results in Table 1.6 are instructive. The first stage results indicate that *Peer Equity Shock* is significantly related to peer firm leverage (columns 1 – 2) and equity issuance (columns 3 – 4) decisions. Further, the F-values for weak instrument tests shown at the bottom of the table are all large and greater than the threshold of 10.

Focusing on the results of the second stage, we find that the coefficient on the instrumented peer average leverage is positive and significant in columns (1)-(2). This is consistent with the presence of peer effects in leverage decisions that propagate through analyst network. Our estimates are also economically significant. The coefficient on *Peer average* in column (2) indicates that a one standard deviation increase in peer firm weighted average leverage is associated with a 0.788 standard deviation increase in the firm's leverage (0.788 = 1.575 * (0.11 / 0.22)).

From columns (3)-(4) we find that the decision of peer firms to issue equity in a year is associated with the own firm's decision to issue equity. We find that the effect of analyst peers is greater than the effect of industry peers. Our estimates are also economically significant. The coefficient estimates indicate that a one standard deviation increase in peer firm average net (gross) equity issuance results in a 12.51% (16.78%) increase in the likelihood of a firm issuing equity as identified by changes in net (gross) equity. In comparison a one standard deviation increase in industry average gross equity issuance (the only coefficient statistically significant) results in a 2.4% increase in the likelihood of a firm making a gross equity issue.

1.5.3 Robustness Tests

Our results thus far suggest that the peer group generated through shared analysts has a direct influence on corporate policy decisions. However, many firms in an analyst network are in the same industry as the firm in question. Leary and Roberts (2014) document the existence of peer effects in leverage among industry competitors. Although we control for industry averages in all our tests, this still raises the question of whether analyst network effects that we document are simply capturing industry peer effects. Our control for industry averages may prove inadequate because the number of analysts in common (which we use to form our weighted average peer equity shock) between pairs of firms in the same industry is higher in comparison to pairs of firms across industries. To the extent that firms in both the same industry and analyst network are more similar and more influential, our analyst peer weighted average may still not be able to fully disentangle industry effects from analyst network effects. We therefore perform several additional tests to address this issue.

In Table 1.7 we re-estimate the reduced form model employing three averages instead of two. These are the weighted average of *Equity Shock* for firms that are both in the same industry and in the analyst network of a firm (Industry=Yes, ACN=Yes), the weighted average of *Equity Shock* for firms which are in the analyst network and not in the same industry (Industry=No, ACN=Yes) and the simple average of *Equity Shock* for firms that are in the same industry but not in the analyst network (Industry=Yes, ACN=No). The construction of these variables can be illustrated with reference to Figure 1. In the figure the numbered shapes represent firms with each shape (*triangle*, *circle*, *etc*) representing an industry. The lines connecting the shapes represent common analysts. Thus the firm *star-0* is connected to six other firms (*star-1, star-2, circle-1, pentagon-1, square-1 and triangle-1*) through common analysts. Of these, *star-1* and *start-2* are in the same industry as *star-0* while the others are in a different industry. Furthermore there are six other firms in the same industry as firm *star-0*. Our first peer average (Industry=Yes, ACN=Yes), for the firm *star-0* is the weighted average of *Equity Shock* for the firms *star-1* and *star-2*. Our second weighted average (Industry=No, ACN=Yes) is calculated across firms *circle-1, pentagon-1, square-1 and triangle-1*. Finally our third average (Industry=Yes, ACN=No) is calculated across firms *start-3* to *star-6*.

In panel A, we report the results using the average *Equity Shock* of firms in the same industry as firm *i*, but not in the same analyst network. Results for leverage and equity issuances are directionally consistent with those in Table 1.4 and in Leary and Roberts (2014), but statistically and economically weaker. Similarly, Panel B shows that leverage and equity issuance decisions are, respectively, negatively and positively related to *Equity Shock* of industry peers in the same analyst network, though these relations are only marginally statistically significant. By contrast, the relations in panel C, where the peer group includes only firms in the same analyst network, but not the same industry, are highly significant and of much larger magnitude. Similar results are found in Panel D, in which all three averages are included in the same specification. Overall, these results suggest that the peer effects operating through analyst networks do not simply reflect industry peer effects.

1.5.4 Placebo Tests.

A potential limitation with the previous analysis is that analysts may choose firms to cover that are economically connected, even if not in the same industry. Thus, firms that are in the same analyst network, but in different industries, may exert influence on one another as a result of their product market connections rather than the analyst connection. In other words, the connection that an analyst creates between firms may proxy for economic linkages between those firms that as researchers we cannot perfectly observe.

We address this concern in Table 1.8 by performing a placebo test. Instead of using the average *Equity Shock* of firms in the same analyst network, we define a set of pseudo peers that are in the same industry as the firms in the analyst network, but do not share a common analyst with firm *i*. Referring to Figure 1, *circle-1, pentagon-1, square-1 and triangle-1* represent firms that are connected to star-0 through common analyst but are in a different industry. To conduct our placebo test, we focus on the firms in the same industry as these firms but that do not have a common analyst with *star-0*. These are firms *pentagon-2* to *pentagon-4*, *square-2* to *square-4* and *triangle-2* to *triangle-4*. We refer to this average as the *Pseudo-peer average* and repeat our tests with this average. If the analyst network captures links across firms in different industries then we should expect the *Pseudo-peer average Equity Shock* to be significantly related to the corporate policies of the firm in question.

The results in Table 1.8 show that there is no significant relationship between *Pseudo-peer average* and a firm's financial policy. This suggests that firms respond to other firms in their analyst network not simply because they are in the same industry or in economically connected industries.

1.5.5 Cross-Sectional Tests

In this section, we perform cross-sectional tests to better illustrate the mechanism underlying the peer effects we document. In these tests, we focus on the level and change in leverage and net and gross equity issuances, as these are the outcome variables for which we find significant peer effects in the previous analysis.

1.5.5.1 Leader vs. Followers

We first examine which firms within an analyst network are most influential. If firms are mimicking one another, we posit that the policy choices of industry leaders will be more influential than those of other firms. In Table 1.9 we identify leader and follower firms within an industry using four alternate criteria. We use *Market share, Profitability*, *Return* and *EPS growth* as the alternate metrics to identify leader and follower firms. We classify a firm as a leader if either its *Market share* and *Return* (only equity issuances) is above sample median or it is in the top quartile in terms of *Profitability*, *Return* (only leverage) or *EPS growth.*[12] We classify all other firms as follower firms. In Panel A we evaluate the

[12]In addition, we use the firms' stock returns (*Return*) in the previous year to identify leaders and follower firms when the dependent variable is either net or gross equity issuances. For the case of leverage, we employ

influence of leader firms on follower firms. That is, the model is estimated on the subsample of firms classified as followers and the independent variable of interest is the average *Equity Shock* of peer leader firms. In panel B we perform the opposite analysis, i.e., we test for the influence of peer follower firms on leader firms.

The results in Panel A of Table 1.9 are similar to those in Leary and Roberts (2014); from columns (1)-(4) we find that irrespective of the criteria used, *Equity Shock* of leader firms in an industry are correlated with market leverage decisions of follower firms.[13] Similar results are obtained for net and gross equity issuances. In Panel B we flip the analysis and test to see if *Equity Shock* of follower firms affect the financial decisions of leader firms. Irrespective of the criteria used, we do not find any significant effect. Thus there is no evidence of social effects from follower firms to leader firms. These results further reinforce our interpretation that the peer effects we document is a result of firms learning from (mimicking) the decisions of the analyst peer firms. In the next set of tests, we differentiate between analysts to better highlight their role in transmitting information across firms.

1.5.5.2 All-star Analysts, Brokerage houses and Analyst Experience

Our paper argues that analyst networks are important in transmitting corporate policy decisions from one firm to another. If this is the case, the characteristics of the analyst herself may be important for the strength of these peer effects. More influential analysts should be more effective at transmitting policy-relevant information across firms. We construct two measures that capture the potential influence of analysts. Specifically, from *Institutional Investor* magazine we collect the information of the top four ranked analysts (first, second, third, and runner-up) for each industry during 1990-2013. We classify an analyst as being influential from the first year she appears in the *Institutional Investor* ranking. We classify brokerage houses that employ two or more influential analysts as *All-star brokerage houses.*

stock returns in the current period.

[13] For brevity we only report the results of leverage in level.

These roughly represent about 10% of all brokerage houses in our sample. We differentiate between all-star brokerage houses and non-all-star brokerage houses to see if there is any difference in the extent of peer effects within their networks. Next we differentiate analysts based on their level of experience. For every year, we calculate the number of years since an analyst first appears on IBES. We then define analysts to have more (less) experience if they are above (below) sample median in terms of the number of years since they first appeared on IBES.

Table 1.10 examines the impact of all-star brokerage houses (Panel A) and analyst experience (Panel B) on the strength of the analyst network peer effect. In Panel A, we use two separate peer averages as independent variables. The first, *Peer Average (All-Star)*, uses only peers that share at least one analyst from an all-star brokerage house. For the second, we use only those peers connected by analysts not from all-star brokerage houses. For each dependent variable (change and level of leverage, net and gross equity issuance), we estimate the model in two ways: a baseline OLS regression in which the peer firm average is the average financial policy of each group of peers, and the reduced form regression in which we employ two weighted average for the *Equity Shock* (All-Star and No All-Star). In all specifications, we find a larger coefficient on peer averages for peers connected through analysts from all-star brokerage houses relative to peers connected through non-all-star brokerage houses. For the OLS regressions, the coefficients are statistically different across the two peer averages. In the case of reduced form regressions, the coefficients are statistically different only for leverage and net equity issuances.

Similar, but stronger, results are obtained in Panel B where we differentiate analysts based on their experience. Here we again form two peer averages, based on firms connected through more (less) experienced analysts. In all specifications, we find stronger peer effects among firms that are connected through more experienced analysts. All of these differences are statistically significant, with the exception of the reduced form model for net equity issuances. Interestingly, in the reduced form models, the peer effect is never statistically different from zero for firms connected through less experienced analysts, but always significant for firms connected through more experienced ones.

1.5.6 Indirect Peer Approach

Finally in Table 1.11 we attempt to isolate the exogenous peer effects from endogenous peer effects by using the friends-of-friends methodology. Specifically, we identify indirect peer firms for every firm. These are firms that are not directly connected to a firm through analyst networks but are connected to one or more of its analyst network peers. We then estimate a two-stage least squares model in which we use the equity shock of these "indirect peers" as an instrument for the financial policies of a firm's direct peers to identify endogenous peer effects in financial policy.

There are several reasons for the equity shock of indirect peers to be exogenous to the financial characteristics of both the firm in question and the direct peer firm. First, the asset pricing model we employ includes market and industry network return factors that are likely to remove common variation due to shocks to the economy or to related groups of firms. Importantly though, not only are the indirect peers in different analyst networks but the vast majority are also in a different industry from the firm in question. Thus, even if the asset pricing model does not completely remove common return shocks, what remains is unlikely to be correlated with the fundamentals of the firm in question. Furthermore, since the indirect peers are in different analyst networks, we can control for the average stock return in each firm's analyst network to further rule out any correlation between the indirect peers' return shocks and the fundamentals of the firm in question. In order to separate contextual from endogenous peer effects, the key identification assumption is that the characteristics of the indirect peers used as instruments are uncorrelated with the characteristics of the direct peers. This is likely to be true for idiosyncratic return shocks as they isolate value-relevant events that are unique to the indirect peers.

The first row of Table 1.11 presents the coefficients on the indirect peer average *Equity Shock* from the first stage. We find that *Equity Shock* of indirect peer firms is significantly related to the level and change in leverage and net and gross equity issuances of direct peers. Further, the F-values indicate that for these policy variables the instrument easily passes the weak instrument test. In the second stage, we find a significant relation between firms' financial policies and those of their direct peers for the level of leverage and both net and gross equity issuances. The positive and significant coefficients on *Peer average* for those corporate policies suggest the average outcome variable of analyst peer firms has a causal effect on a firm's outcome variable. Our results are also economically significant. From the coefficient in column (2) we find that a one standard deviation increase in peer firm average leverage is associated with a 0.352 standard deviation increase in a firm's leverage (0.352 = 0.704 * (0.11 / 0.22)). For equity issuances, we find that a one standard deviation increase in peer firm simple average net and gross equity issuances leads to 13.1% and 29.6% increase in the likelihood of a firm issuing equity, respectively.

It is important to remark that the coefficients associated with industry averages of the outcome variables are also positive and statistically significant but they are smaller in comparison to peer firm endogenous variables. Our results suggest that analyst networks are likely an important source for industry peer effects.

1.6 Conclusion

Sell-side analysts are an important information intermediary in financial markets. There is growing evidence that they may influence the financial policies of firms that they cover. In this paper we provide evidence consistent with sell-side analysts being an important mechanism underpinning peer effects in financial policy choices. Building on recent empirical methods from the network effects literature to identify peer effects, we find that exogenous changes to financial policies of firms covered by an analyst, such as leverage, equity issuance and repurchases, lead other firms covered by the same analyst to make similar changes in policy.

We use an extended Manski-type linear-in-means model, and use the characteristic of indirect analyst peer firms and idiosyncratic equity shocks to peer firms as instruments for analyst peer firm financial policy. We find that firms' leverage and equity issuance decisions are significantly impacted by the peer firms in their analyst network. We show that these network effects are distinct from industry peer effects and that these effects are more pronounced among peers connected by analysts that are more experienced and from more influential brokerage houses. Moreover, less successful firms are more influenced by the financial policies of their more successful analyst peers, but not the other way around.

Research analysts are intermediaries connecting firms to each other. However, firms are also connected by other channels such as social ties or commonality of board of directors, executives, commercial/investment bankers or other professional advisors, and institutional or active investors. The methodology developed in this paper can also be used to identify peer effects in these other settings, and we hope future research will further explore these issues.

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1.8 Appendix A: Variable Definitions

- Book Value of Total Assets: Book value of Assets *(Compustat item: at).*

- Equity Repurchase Indicator: Dummy variable that takes the value of one if equity repurchases normalized by book assets at the beginning of the year is greater than 1% (3%) (5%) *(Compustat items: prstkc/at(t-1)>1%,3%,5%).*

- Equity Shock: Idiosyncratic returns defined as the difference between effective and expected returns based on the methodology provided by Leary and Roberts (2014).

- Gross Equity Issuance Indicator: Dummy variable that takes the value of one if gross equity issuances normalized by book assets at the beginning of the year is greater than 1% (3%) (5%) *(Compustat items: sstk/at(t-1)>1%,3%,5%).*

- Leverage: The ratio of the sum of total long-term debt plus total debt in current liabilities scaled by the market value of assets *(Compustat items:(dltt+dlc)/(prcc_f*cshpri+dlc+dltt+pstkl-txditc)).*

- Log(Sales): Natural logarithmic of sales *(Compustat items: log(sale)).*

- Market-to-Book: The ratio of the sum of the total book value of debt plus market value of equity divided by book value of total assets *(Compustat items: (prcc_f*cshpri+dlc+dltt+pstkl-txditc)/at).*

- Market Value of Assets: The sum of the market value of equity equity plus total long-term debt plus current liabilities *(Compustat items: prcc_f*cshpri+dlc+dltt+pstkl-txditc).*

- Net Debt Issuances: The sum of the total long-term debt plus total debt in current liabilities for the contemporaneous fiscal year minus the sum of the total long-term debt plus total debt in current liabilities in the previous fiscal year *(Compustat items: (dltt+dlc-(dltt(t-1)+dlc(t-1)))).*

- Net Debt Issuance Indicator: Dummy variable that takes the value of one if net debt issuances normalized by book assets at the beginning of the year is greater than 1%. *(Compustat items: (dltt+dlc-(dltt(t-1)+dlc(t-1)))/at(t-1)>1%).*

- Net Equity Issuances: Difference between equity issuances minus equity repurchases *(Compustat items: sstk-prstkc).*

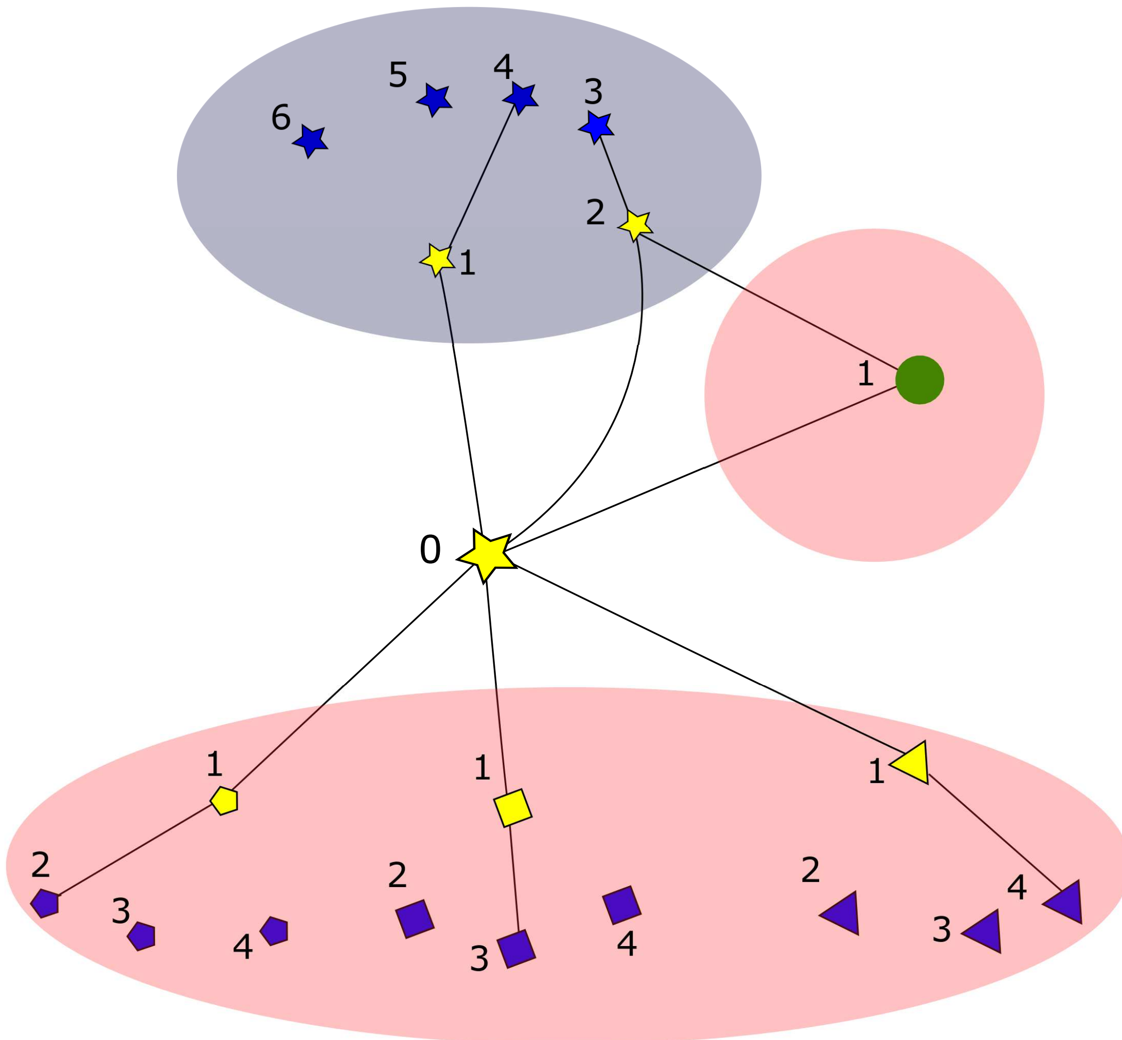
- Net Equity Issuance Indicator: Dummy variable that takes the value of one if net equity issuances normalized by book assets at the beginning of the year is greater than 1% (3%) (5%). *(Compustat items: (sstk-prstkc)/at(t-1)>1%,3%,5%).*

- Profitability: The ratio of the EBITDA divided by book value of total assets *(Compustat items: oibdp/at).*

- Stock Return: Annual return for the firm's stock over the current fiscal year *(Compustat items: ((prcc_f/ajex+dvpsx_f/ajex)/(prcc_f(t-1)/ajex(t-1)))-1).*

- Tangibility: The ratio of the book value of Net Property Plant and Equipment divided by book value of total assets *(Compustat items: ppent/at).*

Figure 1: Analyst Coverage Network



1.9 Figure

1.10 Tables

Table 1.1: Summary Statistics. Analyst Coverage Network and Equity Shock

This table presents the descriptive statistics for the analyst coverage network and the variables used in the regressions analysis. Panel A shows the characteristics of analyst networks in terms of number of connections of direct and indirect peers. Panel B reports the statistics for the outcome variables. Panel C and D show the statistics of the equity shock instrument (lagged one period) and control variables (lagged one period), respectively, used in the regression analysis. All variables used in the regression analysis are winsorized at the 1st and 99th percentile.

Panel A: Analysts Network						
	Number of Connections					
Direct Peers	N	Mean	Std	P25	P50	P75
Overall	37745	41.30	26.86	20.00	37.00	57.00
Within industry	37745	10.46	12.56	2.00	5.00	15.00
Across industries	37745	30.84	25.36	11.00	25.00	45.00
Within industry connection (%)	37745	0.28	0.30	0.05	0.16	0.46
Connected Firms (%)	21	0.94	0.02	0.92	0.94	0.96
Indirect Peers						
Overall	37745	405.54	232.08	218	373	563
Within industry	37745	20.27	32.22	1	5	25
Across industries	37745	385.27	233.1	199	352	541
	Number of analysts in common (Direct Peers)					
Overall	37745	1.89	1.04	1.10	1.50	2.34
Within industry	32326	3.11	2.73	1.18	2.00	4.00
Across industries	36581	1.54	0.72	1.00	1.26	1.78

Panel B: Outcome Variables													
		Firm specific			Industry average			Industry average (No Overlap)			Peer firm simple avg.		
	N	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
ΔMarket leverage	37745	0.01	0.1	0	0.01	0.06	0.00	0.01	0.06	0.00	0.01	0.04	0.00
Market leverage	37745	0.21	0.22	0.15	0.23	0.14	0.20	0.21	0.16	0.16	0.20	0.11	0.19
Net debt issuance (1%)	37745	0.36	0.48	0.00	0.33	0.16	0.30	0.32	0.26	0.29	0.37	0.16	0.36
Net equity issuance (1%)	37745	0.23	0.42	0.00	0.23	0.15	0.22	0.22	0.22	0.19	0.23	0.17	0.19
Gross equity issuance (1%)	37745	0.36	0.48	0.00	0.31	0.18	0.30	0.32	0.27	0.31	0.39	0.23	0.35
		Peer firm weighted average											
		Full sample			Within industry			Accross industry					
ΔMarket leverage	37745	0.01	0.05	0.00	0.01	0.06	0.00	0.01	0.05	0.00			
Market leverage	37745	0.20	0.11	0.19	0.17	0.17	0.13	0.19	0.11	0.18			
Net debt issuance (1%)	37745	0.37	0.18	0.36	0.32	0.30	0.27	0.35	0.20	0.35			
Net equity issuance (1%)	37745	0.22	0.18	0.17	0.20	0.26	0.08	0.21	0.20	0.15			
Gross equity issuance (1%)	37745	0.39	0.24	0.35	0.34	0.34	0.26	0.36	0.25	0.33			

Panel C: Equity Shock	N	Mean	SD	P25	Median	P75
Own equity shock	37745	-0.03	0.50	-0.32	-0.10	0.15
Industry equity shock	37745	-0.03	0.16	-0.12	-0.05	0.04
Industry equity shock (no overlap)	37745	-0.03	0.21	-0.14	-0.04	0.04
Peer equity shock (weighted average)	37745	-0.04	0.12	-0.11	-0.04	0.02
Indirect Peer equity shock (simple average)	37745	-0.03	0.06	-0.07	-0.03	0.00

Panel D: Control Variables													
		Firm specific			Industry average			Industry average (No overlap)			Peer firm simple average		
	N	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median
Log(Sales)	37745	6.69	1.78	6.60	5.78	1.13	5.62	5.81	1.87	5.95	7.07	0.94	7.12
Market to book	37745	1.67	1.26	1.27	1.60	0.66	1.44	1.49	0.81	1.37	1.82	0.75	1.65
Profitability	37745	0.13	0.11	0.13	0.09	0.07	0.10	0.10	0.07	0.11	0.14	0.05	0.15
Tangibility	37745	0.29	0.23	0.22	0.28	0.19	0.22	0.26	0.20	0.20	0.29	0.16	0.26
Δ Log(Sales)	37745	0.10	0.22	0.09	0.10	0.11	0.10	0.08	0.12	0.09	0.11	0.10	0.11
ΔMarket to book	37745	-0.06	0.82	-0.01	-0.07	0.40	-0.05	-0.08	0.43	-0.02	-0.08	0.46	-0.02
Δ Profitability	37745	0.00	0.07	0.00	-0.01	0.03	0.00	0.00	0.03	0.00	0.00	0.03	0.00
Δ Tangibility	37745	0.00	0.04	0.00	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.01	0.00

		Peer firm weigthed average									Indirect peer firm simple average		
		Full sample			Within industry			Across industry					
Log(Sales)	37745	7.24	1.04	7.26	6.20	2.81	6.90	7.06	1.65	7.32	7.15	0.52	7.18
Market to book	37745	1.85	0.82	1.66	1.59	1.16	1.40	1.72	0.79	1.60	1.83	0.57	1.71
Profitability	37745	0.14	0.05	0.15	0.12	0.08	0.13	0.14	0.05	0.15	0.14	0.03	0.14
Tangibility	37745	0.30	0.17	0.26	0.26	0.23	0.18	0.28	0.15	0.26	0.29	0.12	0.27
Δ Log(Sales)	37745	0.11	0.11	0.11	0.10	0.14	0.09	0.11	0.11	0.11	0.11	0.08	0.12
ΔMarket to book	37745	-0.08	0.48	-0.02	-0.07	0.55	0.00	-0.07	0.47	0.00	-0.08	0.38	-0.03
Δ Profitability	37745	0.00	0.03	0.00	0.00	0.03	0.00	0.00	0.03	0.00	0.00	0.02	0.00
Δ Tangibility	37745	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.01	0.00

Table 1.2: Baseline Specification I. Peer Firms vs. Industry

The table presents the OLS estimated coefficients for the baseline regressions. The corporate policies of interest are leverage and debt and equity issuances. The dependent variable is indicated at the top of columns. All the control variables, but excluding *Peer average* and *Industry average*, are lagged one period. When the dependent variable is Δ*Leverage* all the control variables are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. In each column we estimate the regression:

$$y_{ijt} = \alpha + \beta_1 y^{ACN}_{-it} + \beta_2 y^{IND}_{-ijt} + \gamma_1' X^{ACN}_{-it-1} + \gamma_2' X^{IND}_{-ijt-1} + \gamma_3' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

Dependent Variable:	ΔLeverage		Leverage		Net Debt I.		Net Equity I.		Gross Equity I.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Peer average		.555		.372		.215		.316		.284
		(.022)***		(.025)***		(.022)***		(.024)***		(.021)***
Industry average	.461	.253	.405	.286	.218	.166	.307	.215	.346	.262
	(.017)***	(.017)***	(.023)***	(.022)***	(.023)***	(.024)***	(.025)***	(.024)***	(.024)***	(.024)***
Own characteristics										
Log(Sales)	.029	.024	.035	.034	-.043	-.046	-.105	-.100	-.081	-.079
	(.003)***	(.003)***	(.004)***	(.004)***	(.008)***	(.009)***	(.008)***	(.008)***	(.009)***	(.009)***
Market-to-book	.0008	.002	-.019	-.018	.013	.013	.066	.064	.072	.071
	(.0005)	(.0005)***	(.001)***	(.001)***	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***
Profitability	-.033	-.026	-.298	-.297	.354	.347	-.147	-.155	.187	.180
	(.009)***	(.009)***	(.018)***	(.018)***	(.047)***	(.048)***	(.044)***	(.044)***	(.045)***	(.045)***
Tangibility	.095	.089	.071	.076	.313	.320	.085	.087	.051	.049
	(.014)***	(.013)***	(.025)***	(.024)***	(.050)***	(.050)***	(.046)*	(.046)*	(.049)	(.049)
Peer characteristics										
Log(Sales)		.015		-.009		.004		.005		.013
		(.008)**		(.003)***		(.007)		(.006)		(.006)**
Market-to-book		-.004		.006		-.0001		-.005		-.019
		(.001)***		(.002)***		(.007)		(.007)		(.007)***
Profitability		-.044		.081		-.00004		.143		.013
		(.028)		(.037)**		(.105)		(.095)		(.095)
Tangibility		.043		-.061		-.097		.008		.037
		(.045)		(.025)**		(.064)		(.052)		(.055)
Industry characteristics										
Log(Sales)	-.006	-.011	-.009	-.008	-.005	-.003	.002	.0008	-.008	-.008
	(.007)	(.007)	(.005)	(.005)	(.013)	(.013)	(.009)	(.009)	(.012)	(.012)
Market-to-book	-.006	-.003	-.004	-.006	.008	.008	.006	.0004	.003	.006
	(.002)***	(.002)	(.003)	(.003)*	(.009)	(.010)	(.008)	(.008)	(.008)	(.009)
Profitability	.055	.053	.149	.124	.098	.054	.040	.029	-.073	-.096
	(.021)***	(.023)**	(.029)***	(.030)***	(.082)	(.086)	(.071)	(.074)	(.079)	(.083)
Tanigibility	-.062	-.059	.010	.006	-.088	-.054	.054	.024	.061	.041
	(.038)	(.039)	(.043)	(.043)	(.104)	(.105)	(.080)	(.080)	(.093)	(.093)
Obs.	37745	37745	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.149	.176	.778	.783	.241	.243	.392	.398	.458	.463

Table 1.3: Baseline Specification II. Within vs. Across Industry

The table presents the OLS estimated coefficients for the baseline regressions. Moreover, we split the peer average corporate policy and control variables in two depending on the three digit industry classification of peer firms. We calculate the weighted average of corporate policies and control variables for peer firms that are in the same industry classification (within industry) and for peer firms that are in a different industry classification (across industry).The corporate policies of interest are leverage and debt and equity issuances. The dependent variable is indicated at the top of columns. All the control variables, but excluding *Peer average* and *Industry average,* are lagged one period. When the dependent variable is Δ*Leverage* all the control variables are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. In each column we estimate the regression:

$$y_{ijt} = \alpha + \beta_1 \left[y_{-it}^{ACN}\right]_W + \beta_2 \left[y_{-it}^{ACN}\right]_A + \beta_3 y_{-ijt}^{IND} + \gamma_1' \left[X_{-it-1}^{ACN}\right]_W + \gamma_2' \left[X_{-it-1}^{ACN}\right]_A + \gamma_3' X_{-ijt-1}^{IND} + \gamma_4' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

Dependent Variable:	ΔLeverage	Leverage	Net Debt I.	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)	(5)
Peer average (within industry)	.221	.145	.060	.072	.082
	(.014)***	(.016)***	(.012)***	(.014)***	(.013)***
Peer average (across industry)	.277	.149	.084	.162	.139
	(.018)***	(.019)***	(.017)***	(.018)***	(.016)***
Industry average	.265	.291	.166	.231	.260
	(.018)***	(.023)***	(.025)***	(.026)***	(.025)***
Peer characteristics (within industry)					
Log(Sales)	.017	-.006	-.001	-.002	.003
	(.005)***	(.001)***	(.003)	(.002)	(.003)
Market-to-book	-.004	-.0001	-.002	.0008	-.006
	(.001)***	(.002)	(.005)	(.005)	(.006)
Profitability	-.027	.026	.054	-.044	-.088
	(.020)	(.026)	(.078)	(.071)	(.076)
Tangibility	.035	-.027	-.044	.043	-.028
	(.030)	(.019)	(.047)	(.038)	(.043)
Peer characteristics (across industry)					
Log(Sales)	.007	-.003	.0003	.0004	-.001
	(.006)	(.001)**	(.004)	(.003)	(.003)
Market-to-book	.0002	.002	.003	-.013	-.021
	(.001)	(.002)	(.005)	(.005)**	(.005)***
Profitability	-.024	.044	-.077	.204	.153
	(.024)	(.031)	(.090)	(.085)**	(.085)*
Tangibility	.044	-.033	-.043	-.022	.014
	(.039)	(.018)*	(.048)	(.038)	(.039)
Own characteristics	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745
R^2	.169	.781	.242	.396	.461

Table 1.4: Reduced Form using Equity Shock

The table presents the OLS estimated coefficients for the reduced for regression using a modified version of Leary and Roberts (2014) equity shock. The corporate policies of interest are leverage and debt and equity issuances. The dependent variable is indicated at the top of columns. All the control variables and the equity shock instruments are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock instruments, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. In each column we estimate the regression:

$$y_{ijt} = \alpha_0 + \alpha_1 Eq.Shock^{ACN}_{-it-1} + \alpha_2 Eq.Shock^{IND}_{-ijt-1} + \alpha_3 Eq.Shock_{ijt-1} + \gamma_1' X^{ACN}_{-it-1} + \gamma_2' X^{IND}_{-ijt-1} + \gamma_3' X_{ijt-1} + \delta' u_i + \phi' v_t + \epsilon_{ijt}$$

Dependent variable:	ΔLeverage	Leverage	Net Debt I.	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)	(5)
Peer Equity Shock	-.027	-.025	-.029	.059	.077
	(.005)***	(.006)***	(.023)	(.019)***	(.020)***
Industry Equity Shock	-.004	-.015	.009	.008	.028
	(.004)	(.004)***	(.018)	(.013)	(.014)*
Own Equity Shock	-.006	-.016	-.011	.058	.071
	(.001)***	(.002)***	(.005)**	(.005)***	(.005)***
Own characteristics					
Log(Sales)	.028	.035	-.045	-.097	-.075
	(.003)***	(.004)***	(.009)***	(.008)***	(.009)***
Market-to-book	.003	-.017	.014	.059	.065
	(.0006)***	(.001)***	(.004)***	(.004)***	(.004)***
Profitability	-.027	-.295	.360	-.165	.158
	(.010)***	(.018)***	(.048)***	(.044)***	(.045)***
Tangibility	.086	.059	.312	.111	.075
	(.014)***	(.025)**	(.051)***	(.046)**	(.049)
Peer characteristics					
Log(Sales)	.047	-.003	.007	-.011	.002
	(.008)***	(.003)	(.007)	(.006)*	(.006)
Market-to-book	-.004	-.009	-.00009	.016	.004
	(.002)**	(.002)***	(.007)	(.007)**	(.007)
Profitability	-.075	-.063	.071	-.012	.007
	(.029)***	(.038)*	(.106)	(.094)	(.096)
Tangibility	.143	.025	-.059	.021	.012
	(.047)***	(.024)	(.063)	(.052)	(.055)
Industry characteristics	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745
R^2	.118	.771	.238	.393	.459

Table 1.5: Reduced Form. Equity Issuance and Equity Repurchase

The table presents the OLS estimated coefficients for the reduced form using a modified version of Leary and Roberts (2014) equity shock as instrument. The corporate financial policies of interest are equity repurchases and issuances. In columns (1)-(3), (4)-(6) and (7)-(9) the dependent variables are Net Equity Issuance Indicator, Equity Repurchase Indicator and Gross Equity issuance Indicator, respectively. All the control variables and the equity shock instruments are lagged one period. All variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and standard errors are clustered at the firm level. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	Net Equity Issuance			Equity Repurchase			Gross Equity Issuance		
	(1%)	(3%)	(5%)	(1%)	(3%)	(5%)	(1%)	(3%)	(5%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Equity Shock	.059	.055	.041	.040	.027	.019	.077	.053	.046
	(.019)***	(.016)***	(.015)***	(.019)**	(.017)	(.015)	(.020)***	(.018)***	(.016)***
Industry Equity Shock	.008	.008	.012	.006	.008	.020	.028	.013	.009
	(.013)	(.010)	(.009)	(.015)	(.013)	(.011)*	(.014)*	(.011)	(.010)
Own characteristics									
Equity Shock	.058	.045	.039	.001	-.0003	-.0005	.071	.052	.044
	(.005)***	(.004)***	(.004)***	(.005)	(.004)	(.003)	(.005)***	(.005)***	(.004)***
Log(Sales)	-.097	-.081	-.068	.057	.045	.035	-.075	-.077	-.069
	(.008)***	(.007)***	(.007)***	(.009)***	(.008)***	(.007)***	(.009)***	(.008)***	(.007)***
Market-to-book	.059	.054	.042	-.004	.012	.019	.065	.064	.048
	(.004)***	(.004)***	(.003)***	(.004)	(.004)***	(.004)***	(.004)***	(.004)***	(.004)***
Profitability	-.165	-.292	-.286	.629	.562	.454	.158	-.169	-.231
	(.044)***	(.040)***	(.040)***	(.046)***	(.040)***	(.036)***	(.045)***	(.042)***	(.041)***
Tangibility	.111	.165	.170	-.219	-.118	-.086	.075	.154	.171
	(.046)**	(.037)***	(.033)***	(.051)***	(.042)***	(.036)**	(.049)	(.040)***	(.035)***
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.393	.351	.323	.426	.395	.377	.459	.377	.328

Table 1.6: Structural Regression using Equity Shock

The table presents the 2SLS estimated coefficients for the structural regression using a modified version of Leary and Roberts (2014) equity shock as instrument. The endogenous variable is the peer firm weighted average of the dependent variable. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. All the control variables and the equity shock instrument, but excluding *Industry average*, are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. We report the Kleibergen-Paap rk Wald, Cragg-Donald and Anderson-Rubin F-statistics for the weak identification tests.

Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)
First stage :				
Peer Equity Shock	-.013	-.015	.079	.105
	(.002)***	(.003)***	(.007)***	(.008)***
Instrumented peer average	1.785	1.575	.695	.699
	(.429)***	(.477)***	(.228)***	(.180)***
Industry average	-.199	-.090	.108	.134
	(.158)	(.149)	(.068)	(.058)**
Own characteristics				
Equity Shock	-.005	-.015	.058	.070
	(.001)***	(.002)***	(.004)***	(.005)***
Log(Sales)	.019	.028	-.090	-.068
	(.004)***	(.004)***	(.008)***	(.008)***
Market-to-book	.003	-.018	.057	.064
	(.0007)***	(.001)***	(.004)***	(.004)***
Profitability	-.010	-.295	-.183	.152
	(.011)	(.019)***	(.042)***	(.043)***
Tangibility	.077	.097	.100	.063
	(.015)***	(.025)***	(.042)**	(.046)
Peer characteristics	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745
Kleibergen-Paap F-value	48.186	27.013	128.238	172.549
Cragg-Donald F-value	83.952	45.873	264.594	341.505
Anderson-Rubin F-value	21.638	16.309	9.683	15.954
Anderson-Rubin P-value	3.39e-06	.00005	.002	.00007

Table 1.7: Robustness Test

The table presents the OLS estimated coefficients for the reduced form using a modified version of Leary and Roberts (2014) equity shock as instrument. The corporate financial policies of interest are leverage and equity issuances. We include as control variables own and reference group characteristics. All the control variables and the equity shock instruments are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. Panel A, B and C presents the estimated coefficients of the reduced form using the three reference groups independently. Specifically, in Panel A, the coefficients are estimated using as peers all the firms in the same industry as firm i, but they are not in the analysts network of the firm i. In Panel B (C) the coefficients are estimated using as peers all the firms in the same industry (different industries) as firm i, and they are in the network of firm i. Finally, Panel D presents the estimated coefficients of the OLS regressions using the three reference groups all together, industry peers, direct peers within industry and across industries. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	(1)	(2)	(3)	(4)
Panel A: Peer Equity Shock (Industry=Yes, ACN=NO)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer Equity Shock	-.003	-.009	.012	.025
	(.003)	(.003)***	(.010)	(.011)**
R^2	.114	.77	.392	.458
Panel B: Peer Equity Shock (Industry=Yes, ACN=YES)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer Equity Shock	-.005	-.006	.009	.019
	(.003)*	(.003)*	(.010)	(.011)*
R^2	.116	.77	.392	.458
Panel C: Peer Equity Shock (Industry=NO, ACN=YES)				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer Equity Shock	-.014	-.016	.050	.069
	(.004)***	(.005)***	(.016)***	(.016)***
R^2	.115	.769	.392	.458
Panel D: Peer Equity Shock (All together).				
Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
Peer (Industry=Yes, ACN=NO)	-.004	-.009	.012	.024
	(.003)	(.003)***	(.010)	(.011)**
Peer (Industry=YES, ACN=YES)	-.005	-.006	.008	.017
	(.003)*	(.003)*	(.010)	(.011)
Peer (Industry=NO, ACN=YES)	-.016	-.017	.051	.070
	(.004)***	(.005)***	(.016)***	(.016)***
R^2	.118	.771	.393	.459
Obs.	37745	37745	37745	37745

Table 1.8: Placebo Test

The table presents the OLS estimated coefficients for our placebo test using the reduced form specification and a modified version of the Leary and Roberts (2014) equity shock as instrument. We use industry peers of firms in the network of firm i, but we do **NOT** include firms in the same industry of firm i. The exogenous variable is the *Pseudo-peer Equity Shock*. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. All the control variables and the equity shock instrument are lagged one period. When the dependent variable is $\Delta Leverage$ all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable:	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)
Pseudo-peer Equity Shock	-.003	-.013	.002	.021
	(.011)	(.013)	(.037)	(.040)
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Pseudo-peer characteristics	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745
R^2	.114	.769	.392	.458

Table 1.9: Leaders vs. Followers

The table presents the OLS estimated coefficients for the reduced form. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. We classify leader and followers based on their within industry-year ranking associated to market share, EPS growth, profitability and stock return. A firm is classified as industry leader if it belongs to the top quarter in each industry-year subsample for the case of EPS, Profitability and stock return (only for leverage) and a firm is classified as leader when its market share and stock return (only for equity issuances) is above the median. All the control variables and the equity shock instruments are lagged one period. The exogenous variable is the weighted average *Equity Shock* of peer leader (follower) firms. Panel A(B) shows the effects of leader (follower) firms on individual follower's (leader's) corporate policy decisions. All variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and standard errors are clustered at the firm level. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Leaders affect Followers												
Follower Firm Dependent Variable:	Leverage				Net Equity Issuance (1%)				Gross Equity Issuance (1%)			
	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Peer Equity Shock (Leaders)	-.022	-.010	-.016	-.008	.061	.020	.032	.039	.062	.013	.034	.021
	(.009)**	(.003)***	(.004)***	(.004)**	(.028)**	(.010)**	(.014)**	(.019)**	(.029)**	(.010)	(.014)**	(.020)
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14150	29938	28586	29710	14150	29938	28586	19360	14150	29938	28586	19360
R^2	.801	.782	.781	.788	.457	.405	.42	.433	.493	.482	.46	.493
Panel B: Followers affect Leaders												
Leader Firm Dependent Variable:	Leverage				Net Equity Issuance (1%)				Gross Equity Issuance (1%)			
	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return	Market Share	EPS growth	Profitability	Return
Peer Equity Shock (Followers)	-.006	-.013	-.011	-.012	.015	.011	.013	.014	.002	.066	.050	.047
	(.004)	(.019)	(.008)	(.017)	(.013)	(.061)	(.040)	(.031)	(.013)	(.063)	(.039)	(.032)
Own characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics (incl. Eq. Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23595	7807	9159	8035	23595	7807	9159	18005	23595	7807	9159	18005
R^2	.782	.846	.832	.851	.395	.616	.516	.501	.48	.639	.587	.548

Table 1.10: All-Star Brokerage Houses and Analyst Experience

The table presents the OLS estimated coefficients for the baseline regression (BR) and reduced form (RF) using a modified version of the Leary and Roberts (2014) equity shock as instrument. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns. We classify analysts with larger experience if within a year the number of years that they appear on IBES is above the median. For the case of all-star brokerage houses, we classify them according to the number of all-star analysts that they employ (at least two all-star analysts, which is approximately the top decile of the distribution). We calculate the weighted averages of the *Equity Shock*, outcome and control variables for peer firms that share at least one analysts with larger experience (all-star brokerage houses) and for peer firms that do not share any analysts with larger experience (brokerage houses). Panel A display the results with respect to all-star brokerage houses and Panel B shows the results using analyst experience. All the control variables and the equity shock instruments, but excluding *Peer and Industry average*, are lagged one period. When the dependent variable is Δ*Leverage* all the control variables, except the equity shock, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. All variables are winsorized at the 1st and 99th percentile. For brevity we suppress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: All-Star Brokerage Houses (All-Star vs. No All-Star)								
Dependent Variable:	ΔLeverage		Leverage		Net Equity I.		Gross Equity I.	
	BR	RF	BR	RF	BR	RF	BR	RF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer average (All-Star)	.512		.354		.251		.237	
	(.019)***		(.022)***		(.022)***		(.019)***	
Peer average (No All-Star)	.225		.126		.138		.126	
	(.017)***		(.017)***		(.017)***		(.016)***	
Peer Equity Shock (All-Star)		-.019		-.024		.060		.059
		(.005)***		(.006)***		(.019)***		(.020)***
Peer Equity Shock (No All-Star)		-.014		-.009		.003		.031
		(.004)***		(.004)**		(.014)		(.015)**
(All-Star)-(No All-Star)	0.287	-0.006	0.228	-.015	0.114	0.057	0.111	0.027
P-value	**0.000**	0.364	**0.000**	**0.038**	**0.000**	**0.012**	**0.000**	0.262
Industry average (No overlap)	Yes	No	Yes	No	Yes	No	Yes	No
Industry Equity Shock	No	Yes	No	Yes	No	Yes	No	Yes
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (All-Star)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (No All-Star)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.169	.118	.78	.771	.4	.394	.465	.459

Panel B: Analyst Experience (Larger vs Smaller)								
Dependent Variable:	ΔLeverage		Leverage		Net Equity I.		Gross Equity I.	
	BR	RF	BR	RF	BR	RF	BR	RF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer average (Larger)	.570		.401		.293		.282	
	(.020)***		(.024)***		(.022)***		(.019)***	
Peer average (Smaller)	.132		.062		.073		.058	
	(.014)***		(.012)***		(.013)***		(.012)***	
Peer Equity Shock (Larger)		-.027		-.027		.042		.067
		(.005)***		(.006)***		(.019)**		(.020)***
Peer Equity Shock (Smaller)		-.004		-.005		.014		.019
		(.003)		(.003)		(.011)		(.012)
(Larger)-(Smaller)	0.438	-0.023	0.339	-0.022	0.219	0.028	0.224	0.048
P-value	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	0.195	**0.000**	**0.036**
Industry average (No overlap)	Yes	No	Yes	No	Yes	No	Yes	No
Industry Equity Shock	No	Yes	No	Yes	No	Yes	No	Yes
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (Larger)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Peer characteristics (Smaller)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745	37745	37745	37745	37745
R^2	.168	.118	.78	.772	.401	.394	.465	.459

Table 1.11: Indirect Peer Firms and Structural Regression

The table presents the 2SLS estimated coefficients for the structural regression using indirect peer firms equity shock as instrument. In addition, we employ a modified version of the Leary and Roberts (2014) equity shock. The endogenous variable is the peer firm simple average of the dependent variable. The corporate financial policies of interest are leverage and equity issuances. The dependent variable is indicated at the top of columns All the control variables and instruments, but excluding *Industry average (no overlap)*, are lagged one period. When the dependent variable is Δ*Leverage* all the control variables, except the equity shock and peer average stock return, are also in first differences and we include year and industry fixed effect. The remaining regressions include firm and year fixed effects. Standard errors are clustered at the firm level. For brevity we supress the constant. See Appendix A for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis. We report, the Kleibergen-Paap rk Wald F statistic, Cragg-Donald F statistic and Anderson-Rubin F-statistic for the weak identification tests.

	ΔLeverage	Leverage	Net Equity I.	Gross Equity I.
	(1)	(2)	(3)	(4)
First Stage: Indirect peers'				
Equity Shock	-.034	-.048	.106	.161
	(.004)***	(.007)***	(.016)***	(.018)***
Instrumented peer average	.462	.704	.770	1.287
	(.349)	(.305)**	(.459)*	(.324)***
Industry average (No overlap)	.119	.033	.038	.025
	(.046)***	(.014)**	(.020)*	(.015)
Peer average stock return	.0003	-.008	.007	-.030
	(.007)	(.006)	(.040)	(.030)
Own characteristics (incl. Equity Shock)	Yes	Yes	Yes	Yes
Peer characteristics	Yes	Yes	Yes	Yes
Ind. characteristics	Yes	Yes	Yes	Yes
Obs.	37745	37745	37745	37745
Kleibergen-Paap F-value	57.042	45.865	44.978	75.613
Cragg-Donald F-value	92.994	69.487	77.211	129.445
Anderson-Rubin F-value	1.647	5.252	2.883	17.988
Anderson-Rubin P-value	.199	.022	.09	.00002

Chapter 2

Analyst Coverage Network and Stock Return Comovement in Emerging Markets

2.1 Introduction

Stock return comovements and stock market linkages in emerging markets have been a source of great interest for researchers, policy makers and investors (Bekaert and Harvey (2003), Forbes and Rigobon (2002), Rigobon (2002)). When portfolio managers and retail investors decide on an asset allocation strategy they consider the potential advantages of portfolio diversification within and across countries. For that reason, many researchers are interested in the level of correlation among financial markets and their main determinants (Lahrech and Sylwester (2011), Chen et al. (2002) and Bekaert et al. (2005)). Financial crises in developed and emerging countries, changes in investor regulation, financial integration and cross-sectional characteristics of countries have been exploited to test changes in excess comovement of stock returns and synchronicity (Morck et al. (2000), Jin and Myers (2006), Bae et al. (2012) and Balli et al. (2015a)). In this paper we want to introduce a new source of excess comovement between pairs of stocks across Latin American countries. Specifically, we are interested in the effects of information produced and disseminated by analysts following simultaneously a pair of firms i and j on stock return comovement and excess comovement.

Using panel data at firm-pair level we depart from the traditional literature in international finance that looks at changes in excess comovement among equity or industry indexes. We provide evidence about the informational importance of analyst coverage networks, specifically common coverage, in explaining the excess of correlation between pairs of stocks with shared coverage. We show that if investors trade based on information provided by analysts the stock return pairwise correlation between firm i and j is positively associated with the number of analysts they have in common. That is because analysts produce and disseminate common information (useful) for firm i and j. Muslu et al. (2014) called this *the coverage-specific information spillover hypothesis.* In addition, the authors argue that analysts face a trade-off between the type of information that they produce and the cost of producing it. For that reason, analysts produce a mix of three type of information. On one side, firm-specific information which is highly rewarded by investors, however it requires more time and effort. On the other side, market-wide (broad) information which has lower production costs, but it has less impact on investors, given that other analysts can produce the same information. In the middle, though, the *coverage-specific information* which is relevant information for the pool of firms that an analysts is following. Analysts, in order to reduce production costs, provide information that emphasizes commonalities among stocks in their coverage.

In addition, if an analyst uses the same model, inputs or methodology to make earnings forecasts for the pool of firms that she follows the error term contained in the signal will be correlated which increases stock commonalities (Israelsen (2014)). In other words, under rational Bayesian updating investors cannot completely differentiate the error component from the signals and cannot identify the correlation in forecast errors. Hence, investors will update their beliefs and trade based on those signal increasing the return correlation between pair of firms if the error terms of the earnings forecast are positively correlated. Following Muslu et al. (2014) and Israelsen (2014) we create two measures of common coverage and provide evidence that comovement and excess comovement between pairs of stocks within and across countries in emerging markets can be explained by the network created by analysts. Specifically, the common information generated by analysts influences the investor demand affecting the commonality in returns.

Sell-side analysts are important intermediaries in financial markets. They play a key role in acquiring, analyzing, producing and disseminating useful information for investors and managers' decisions (Frankel et al. (2006)). Moreover, analysts provide different types of information such as firm-specific, industry-wide and coverage-specific information (Yu (2008), Kadan et al. (2012), Muslu et al. (2014), Chan and Hameed (2006) and Piotroski and Roulstone (2004)). Hence, analysts, as information intermediaries, connect the firms that they cover through the information channel. In addition, analysts are an important source of external monitoring; they serve as substitutes for internal monitoring in firms with weak corporate governance (Chen et al. (2015)). And, there is a vast literature providing evidence of the effects of analysts on corporate policies, corporate governance, financial reporting quality, cost of capital, firm opacity and M&A terminations (Becher et al. (2015) Derrien and Kecskés (2013a), Chen et al. (2015), Kelly and Ljungqvist (2012), Irani and Oesch (2013) and Gomes et al. (2015)).

The role of analysts has been studied assuming that analyst coverage has only isolated effects on firms that they follow. However, a growing literature shows that analyst coverage is an important determinant in how firms interact and affect each other. Analysts tend to follow firms with similar characteristics and choose a pool of firms according to their skills and preferences to produce the most useful information possible. But they also produce common information and monitor the firms in a similar manner. Moreover, analysts influence investor demand through their recommendations and earnings forecast. If investors trade based on analyst information and recommendations, analysts implicitly perform a relative valuation of firms that they follow, which in turns affects investor demand. Kaustia and Rantala (2015) use firms connected by analysts in common as the direct peers rather than industry peers to show how social interactions affect stock split decisions. Gomes et al. (2015) work with direct and indirect peer firms (friends' friends approach) according to analyst networks to provide evidence of peer effects on corporate financial policies. In addition, the paper is directly related to Israelsen (2014) and Muslu et al. (2014). They study analyst networks and provide evidence of comovement and excess comovement for pairs of firms with analysts in common for the US market. They also find stock returns comovement between pairs of firms that share common analysts, and they argue that the comovement is likely due to the fact that the information produced by common analysts is available to all firms in their coverage universe (*coverage-specific information*).

In this paper we are interested in analyst coverage networks in Latin America as an important channel (information) in which shared coverage affects stock return comovement for pairs of stocks across and within countries. We construct the analyst coverage networks for Latin American countries such as Argentina, Brazil, Chile, Colombia, Mexico and Peru to address the research question: *Do firms with higher shared analyst coverage have more stock return comovement and excess comovement as compared to firms which do not have common analysts?* The motivation of this paper is to show that analysts are important in explaining contagion among financial markets and pairs of stocks.

The effect of analysts on emerging markets has been widely studied focusing on the role of analysts as financial intermediaries who reduce asymmetric information between investors and firm and improve the information environment for investors' sake. Chan and Hammed (2006) and Fernandes and Ferreira (2008) document the effect of analysts on stock return synchronicity and market-wide information. They show that analysts in emerging markets provide market-wide information rather than firm specific information. On the contrary, Bae et al. (2006) show that analyst coverage increases after stock market liberalizations and its contribution to the information environment after openness is more important. Moshirian et al. (2009) examine abnormal returns associated with post-recommendation buy and hold in emerging markets. They find stock returns react strongly to stock analyst recommendations and revisions. Lai and Teo (2008) and Bae et al. (2008) study the difference between local and foreign analysts. For instance, domestic analysts are more optimistic and have more accuracy than foreign analysts. Moreover, David and Simonovska (2015) show how the role of correlated beliefs on the part of investors (using earnings forecast as the proxy variable) are strongly related to excess return correlations in developed and emerging markets.

We follow Israelsen (2014) and Muslu et al. (2014) and create two variables for shared coverage. Also, we test our hypothesis using raw returns in local currency and US dollars. To calculate the excess comovement we obtain the idiosyncratic returns using the augmented market model regression. We use four different specifications which consider local index market returns, local industry returns, US market returns and MSCI Latin American index returns.

Our final sample comes from four sources. We use I/B/E/S (non-US file) to obtain information about the analyst coverage for Argentina, Brazil, Chile, Colombia, Peru and Mexico. From Worldscope we collect financial information and from Datastream we obtain daily and weekly stock return information. We acquire the MSCI Latin American constituents using Bloomberg. Our sample spans the period 2000-2014 having 27,833 and 50,221 firm-pair-year observations within and across countries, respectively.

In terms of the research question, our results show that pairs of stocks that are connected by analysts in common have greater raw return correlation and excess comovement as compared to firms that do not share any analysts. Also, we provide different cross-sectional tests to support the hypothesis that investors find useful the information provided by analysts. In terms of economic significance, one standard deviation increase in the shared coverage rises by 1.5% the pairwise correlation of weekly return (comovement) denominated in local currency when we consider the full sample. Moreover, using weekly returns denominated in US dollars the correlation increases by 1%. Regarding the excess comovement, one standard deviation increase in the shared coverage rises on average by 2% the excess comovement when we consider the full sample.

We perform additional cross-sectional tests finding that the effect of analyst coverage networks is larger for pairs of stocks that belong to the MSCI Latin American Index. These results suggest that when investors face fewer trade restrictions the information is better reflected in prices inducing a higher level of excess comovement. Moreover, we test the effect of domestic and international analysts on commonalities of stocks across and within countries. We provide evidence that international analysts are the source of excess comovement on pairs of firms across countries, but within countries domestic and international analysts have similar effects.

A valid concern regarding these results is that the formation of the ACN is endogenous. Analysts choose the pool of firms to follow based on unobserved analysts and/or firm characteristics. Also, analysts tend to choose firms with similar characteristics or with the same risk exposure. Hence, the cross-sectional results might capture unobserved common risk or characteristics between the pairs of firms. In order to alleviate these concerns we exploit the changes in the MSCI Latin American Index composition. Being added to the MSCI index represents a positive shock for Latin American firms. Every June and December the index changes its constituents according to their market capitalization and insider ownership (free float). When firms are incorporated to the index the investor demand for those firms grows and also investors tend to demand more information, which increases the number of analysts following those firms. We identify all the firms that are incorporated in the index and calculate the change in their coverage. We find that firms incorporated in the index show an increase in the number of analysts covering the stock. More importantly, the number of analysts in common between those firms and their peer firms (connected by shared coverage) is also increased. Then, we provide evidence that increases in the shared coverage affect positively the cross-sectional relation between changes in common analyst coverage and changes in excess comovement.

Moreover, we test whether brokerage house connections rather than analyst connections are more important. Calculating the brokerage coverage network within and across countries we find that there is a positive relation between common coverage and stock return commonalities, but the results are not as strong as for the analyst coverage network. We depart from the stock return comovement framework by looking at the stock price synchronicity. Specifically, we test whether stock returns of peer firms, connected by shared coverage in different countries, explain individual firm returns. We find that peer firms across countries have a positive effect on stock return synchronicity. These results support our hypothesis that the coverage-specific information propagated to the network matters.

Finally, the contribution of this study is twofold. First, we show that common coverage is an important determinant in explaining stock return commonalities in emerging markets through the information channel. In addition, we go further by showing that comovement and excess comovement at pair of firms level. Previous studies use, mainly, indexes and aggregated data. Moreover, the information role of analysts is the keystone in this study. Hence, the paper contributes to the current literature associated with the role of analysts as financial intermediaries between investors and firms. However, this paper is focused on the *coverage-specific information* rather than firm-specific or market-wide information. The second contribution of this paper is related to the role of networks in explaining financial contagion, commonalities and corporate policies in emerging markets. Specifically, our network based on common coverage is an important dimension in which firms are connected. For that reason, this paper helps to understand better how connections between firms make them affect each other.

The rest of the paper is organized as follows. Section 2.2 discusses the related literature and the hypothesis. Section 2.3 explains our data and empirical methodology. Section 2.4 provides the summary statistics, section 2.5 discusses the empirical evidence and section 2.6 concludes. Definitions of empirical variables are in Appendix B.

2.2 Literature Review and Hypothesis Development

This paper is related to three streams of literature. The first is with respect to contagion and stock comovement across financial markets. The second is the role of analysts in developed and emerging financial markets as information intermediaries between investors and firms, and the third explores the effect of social networks on corporate policies and stock return comovement. Thus, this study contributes to the literature by showing that shared coverage is an important determinant that explains comovement and excess comovement between pairs of stocks in the same (within) and different (across) countries.

The first stream of literature is the stock return correlations in emerging markets. Stock return comovements and stock market linkages in emerging markets have been a source of great interest among researchers, policy makers and investors (Bekaert and Harvey (2003), Forbes and Rigobon (2002), Rigobon (2002)). When portfolio managers and retail investors decide the asset allocation strategy they consider the potential advantages of portfolio diversification within and across countries. For that reason many researchers are interested in the level of correlation among financial markets and their main determinants (Lahrech and Sylwester (2011), Chen et al. (2002) and Bekaert et al. (2005)). Financial crises in developed and emerging countries (Aloui et al. (2011), Guo et al. (2011) and Baur (2012)), changes in investor regulation (Phylaktis and Ravazzolo (2005)), financial integration, cross-sectional characteristics of countries and bilateral links between countries (Balli et al. (2015b)) have been exploited to test changes in stock return comovement and synchronicity (Morck et al. (2000), Jin and Myers (2006)) and transmission of market shocks. Recently studies have addressed how news around the world affect stock return commonalities (Dang et al. (2015)) and how foreign investors help to facilitate information transmission in emerging markets (Bae et al. (2012)). Moreover, firms that are cross-listed and/or are members of MSCI indexes face higher demand of international investors which increases the stock return comovement between stock due changes in inflows/outflows of foreign investors (Raddatz and Schmukler (2012), Raddatz et al. (2015) and Bartram et al. (2015)).

Regarding to studies with a focus on Latin American countries. Chen et al. (2002) investigate the dynamic interdependence of the major stock markets indexes in Latin America (Argentina, Brazil, Chile, Colombia, Mexico and Venezuela). Lahrech and Sylwester (2011) examine to what extent the Latin American equity markets have become more integrated with the US equity market. In the same line Hunter (2006) analyze how Latin American markets become more integrated in the post-liberalization period. Diamandis (2009) examines long-run relationships between Argentina, Brazil, Chile and Mexico stock markets and the US market. Additionally, recent papers study the effect of major Latin American financial crisis and recent subprime crisis on stock markets' volatility spillovers and co-integration (Aloui (2011), Barba and Ceretta (2010)).

The second stream is related to the role of analysts in the financial markets as information intermediaries between investors and firms. They play a key role in acquiring, analyzing, producing and disseminating useful information for investor and manager decisions (Frankel et al. (2006)). Moreover, analysts provide different types of information such as firm-specific, industry-wide and *coverage-specific information* (Kadan et al. (2012); Chang et al. (2006); Piotroski and Roulstone (2004); Muslu et al. (2014)). Also, through monitoring they reduce the asymmetric information between insiders and outsiders and also between informed and uninformed investors. Firms become more transparent and firm-specific information increases when firms have more analysts covering them (Yu (2008) and Crawford et al. (2012))

At the same time, analysts affect corporate financial policies. Degeorge et al. (2013) and Derrien and Kecskés (2013b) provide evidence that analyst coverage and preferences have important effects on corporate policy decisions. Becher et al. (2015) show that recommendation revisions can reduce (increase) the propensity to complete M&A when analysts make downwards (upwards) revisions after the announcement of the M&A. Chang et al. (2006) show that firms with lower analyst coverage prefer to issue more debt as compared to equity issuance, because firms with lower coverage face more information asymmetry between insiders and outsiders. Moreover, in better market conditions, firms with lower coverage (higher information asymmetry) tend to issue more equity, supporting the market timing theory. Fracassi et al. (2014) show how analyst subjectivity affects credit ratings and corporate debt pricing. Hong and Kacperczyk (2010) identify an exogenous source of variation in analyst coverage and they provide evidence that a decrease in the analyst coverage reduces the competition in the analysts' market. This reduction exacerbates the analysts' optimism bias and thus the quality of the information they produce. Kelly and Ljungqvist (2012) use the same quasi-experiment that Hong and Kacperczyk (2010) use, but they incorporate brokerage closures and provide evidence that a reduction in the number of analysts increases the asymmetric information of the firm between insiders and outsiders (shareholders and managers).

The effect of analysts on emerging markets has been widely studied with a focus on how analyst information affects market efficiency. Chan and Hammed (2006) document the effect of analysts on stock return synchronicity. They show that analysts in emerging markets provide market-wide information rather than firm specific information. In the same line, Fernandes and Ferreira (2008) show that firms from emerging markets face a higher coverage when they cross-list their shares in the U.S. However, more analyst following increases the market-wide information instead of increasing the specific-firm information. On the contrary, Bae et al. (2006) show that analyst coverage increases after stock market liberalizations and its contribution to the information environment after openness is more important. However, the authors suggest that openness and the increase in analyst coverage improve the information environment increasing the firm-specific information. Regarding the impact on prices of the information produced by analysts. Moshirian et al. (2009) examine abnormal returns after buy and hold recommendations in emerging markets. They find stock prices react strongly to stock analyst recommendations and revisions. In addition, other authors study the difference between domestic and international analysts. For instance, Lai and Teo (200) compare local versus foreign analysts showing a home bias effect. Domestic analysts are more optimistic and local analyst upgrades underperform foreign analyst upgrades, while local analyst downgrades outperform foreign analyst downgrades. Moreover, using analysts' earnings forecast data of 32 developed and emerging countries, Bae et al. (2008) show that local analysts have more accuracy than than foreign analysts making earnings forecast. Finally, this study is highly connected to the evidence provided by David and Simonovska (2015). They show how the role of correlated beliefs on the part of investors (using earnings forecast as the proxy variable) are strongly related to excess return correlations in developed and emerging markets.

This paper is closely related to the growing literature that uses social interaction to explain return commonalities. Intermediaries can affect the correlation between pairs of firms due to the information that they provide or the investment decisions that they make. Grullon et al. (2014) use investment bank networks to provide evidence about stock return comovement of firms that share the same investment bank. The hypothesis is that market segmentation can lead to the formation of networks. These networks emerge because clients of investment banks (investor) concentrate their holdings and trading patterns in a defined pool of securities induced by the advice and information provided by the banks. Anton and Polk (2014) use mutual funds to create networks based on the ownership of different active mutual funds on the same stocks. They show show that the degree of shared ownership forecasts cross-sectional variation in return correlation. In terms of theoretical models, Caccioli et al. (2014) develop a model to understand better the amplification of financial contagion due to the combination of overlapping portfolios and leverage. The authors create a network based on common asset holding between investors (banks). Moreover, other important networks are used to explain and determinant the extent of financial contagion. Banks, international trade and mutual funds are used to create networks (Summer (2013), Glasserman and Young (2015b) and Glasserman and Young (2015a)).

The following two papers provided the theoretical background for our empirical evidence. First, Muslu et al. (2014) find stock returns comovement between pairs of firms that share analysts and provide evidence of stock return synchronicity for stock portfolios with the same analyst coverage. They argue that analysts provide *coverage-specific information*, which is common information for the pool of firms that each analyst follows. Firms can have common factors, such as common risk, common inputs or their business models are related in some dimension. Hence, when a analyst produces information for one firm that information might also be useful for other firms that the analyst follows. The *coverage-specific information* concept is a middle point between firm-specific information and market-wide (broad) information.

Israelsen (2014) works with analyst coverage networks to provide evidence of excess comovement for pairs of stocks with analysts in common for the US market. The author argues that if an analyst uses the same model, inputs or methodology to make an earnings forecast, the error term contained in the signals (earnings forecast for firm i and j) for both firms will be positively correlated. This connection increases the stock return pairwise correlation because investors will trade based on the new information without completely identifying the error component in the forecasts. In other words, under rational Bayesian updating investors cannot completely differentiate the error component from the signal and cannot fully identify the correlation in the forecast errors. Hence, investors will update their beliefs and trade based on those signal increasing the return correlation between pair of firms if the error terms of the earnings forecast (signals informative about the means) are positively correlated. We based our research question on Israelsen (2014) and Muslu et al. (2014) to provide evidence that stock return comovement and excess comovement between pairs of stocks within and across countries can be explained by the analyst coverage network. Specifically, the common information generated by analysts influences the investor demand.

2.3 Data and Empirical Methodology

We construct a comprehensive sample at the intersection of Worldscope, Datastream, Bloomberg and I/B/E/S databases.[1] We obtain analyst coverage information for the six countries mentioned above from I/B/E/S. The stock price information is obtained from Datastream and the financial information and insider ownership from Worldscope. Also, the MSCI Latin American index and its members are obtained from Bloomberg.

We exclude financial firms (SIC codes between 6000 and 6999) and and government companies (SIC codes greater than or equal to 9000). Our final sample contains 256 Latin American firms and spans the period 2000-2014.[2] Our Worldscope-Datastream-I/B/E/S-Bloomberg data set contains 27,833 and 50,221 firm-pair-year observations within and across countries, respectively.

We identify an analyst as following a firm in a fiscal year if she makes at least one earnings forecast during the year and the forecast is made no more than six months before the end of the fiscal period and at least three months after the end of the fiscal period.[3] Then we create the analyst coverage network calculating the number of analysts in common (N_p) for each pair (p) of firms i and j.

Since our main dependent variable is the comovement between pairs of firms, we will run the pair model regression. The pair model uses each pair of companies in the sample

[1]Worldscope contains the SEDOLs and I/B/E/S unique identifier (TICKER). Thus, we first merge Worldscope with I/B/E/S using the TICKERs. Then, we merge Worldscope-I/B/E/S dataset with Datastream and Bloomberg using SEDOLs.

[2]Number of firms per country: Argentina(18), Brazil(118), Chile(48), Colombia (10), Mexico (52) and Peru (10).

[3]Usually in Latin American firms the fiscal year is the same as the calendar year (fiscal year ends in December).

as the unit basis of analysis (Fracassi (2016)).

$$y_{p,t} = \alpha + \beta_1 * ACN_{p,t} + \gamma * X_{p,t} + \lambda_{pkt} + \delta_{pct} + e_{pt} \tag{2.1}$$

Where p refers to the pair of firms i and j. Also, the subscripts t, c and k refer to year, country and industry, respectively. The dependent variable, $y_{p,t}$, measures either comovement or excess comovement between firm i and j in the calendar year t (we explain the measures below). $ACN_{p,t}$ is our variable of interest which is the analyst coverage network. We use two definitions for $ACN_{p,t}$. Muslu et al. (2014) use the number of analysts in common (N_p) between pair of firms (p) i and j divided by the total number of analysts covering either stock in the pair; we call this measure $NumA_{p,t}$. Moreover, Israelsen (2014) considers the number of analysts in common between pairs of firms and also the total analyst coverage of each firm independently. The measure is defined as follows:

$$RhoA_{p,t} = \frac{N_p}{\sqrt{N_i N_j}}$$

Where N_i and N_j represent the total number of analysts following firms i and j, respectively. According to Israelsen (2014), $RhoA_{p,t}$ is a proxy for the correlated earnings forecasts errors (signals) between pair of firms that share analysts in common. In our regression analysis, we calculate the pairwise stock correlation for all the pairs of firms with analyst coverage $N_i, N_j > 0$ even though they do not share any analysts at all (N_p=0).[4] Hence, in our final sample the two measures fall in the interval $[0, 1]$.

In the matrix $X_{p,t}$ we control for a battery of firm-specific characteristics that are likely to be correlated with the stock return comovement (See Appendix B for more details about the variables definition). Regarding firm financial-accounting characteristics we control for *Log(Sales)*, *Market-to-Book ratio*, *ROA*, *ROE*, *Leverage*, *Log(MKTCAP)*, *Stock Price* and *EPS*.[5] Also, we use three variables to control for stock characteristics that might affect infor-

[4] We consider all the pair combinations for firms that have at least one common analysts following them. In other words, we use only firms that appears in the I/B/E/S data set with valid annual earnings forecasts.

[5] All the financial-accounting variables are in US dollars.

mation transmission and stock return comovement. PADR (PMSCI) is a dummy variable that takes the value of one if the pair of firms i and j are cross-listed on a U.S. stock exchange (belong to the MSCI Latin American Index) in the same fiscal year. PADR and PMSCI are important variables to control for correlation induced by the international investors demand. When firms are cross-listed and/or are members of MSCI indexes the demand of international investors is higher, which increases the stock return comovement between stocks due to changes in inflows/outflows of foreign investors (Raddatz and Schmukler (2012) and Bartram et al. (2015)). In addition, we control for insider ownership (CHO), which is a variable that measures the proportion of a firm's shares that are closely held (CHO) by insiders and controlling shareholders (Dang et al. (2015)). CHO is also a proxy for the degree of accessibility of foreign investors to emerging stock markets. Bae et al. (2012) show that greater investability reduces price delay to global market information. When the fraction of shares closely held by insiders and controlling shareholders is larger it becomes more difficult for foreign investors to trade based on global information affecting market efficiency.

We include additional variables related to stock characteristics such as Annual Return (AnnRet) and daily stock price volatility (Volatility). Also, following Bekaert et al (2007) and Bartram et al. (2015), we incorporate two liquidity measures. We use the percentage of zero return (PZR) and the number of days that the stock was traded (NDays). Since we are using the pair model for each pair of companies i and j, we follow the procedure explained by **?** and we control for the the absolute difference of the measures explained above (except for the dummy variables). Also we control for country-pair-year fixed effects (δ_{pct}) and industry-pair-year fixed effects (λ_{pkt}) using two digit-SIC code. The former helps us to control for differences in country characteristics in each year and the latter controls for difference in industry characteristics in each year. It is important to highlight that when we run the model for only pairs of firms within countries the country-pair-year fixed effects (δ_{pct}) are just equivalent to country-year fixed effects. In addition, all the control variables used in the regression analysis are winsorized at the 1st and 99th percentile.

Regarding the dependent variable ($y_{p,t}$), we use weekly returns in local currency and US dollars to calculate the pairwise correlation of raw returns and the correlation of idiosyncratic returns to calculate comovement and excess comovement, receptively. To calculate the latter, we run an augmented market model regression using two different specifications:

Model 1: $R_{it} = \alpha + \beta_1 R_{mt} + \beta_2 R_{ind,t} + \beta_3 R_{MSCI,t} + \beta_4 R_{US,t} + e_{it}$

Model 2: $R_{it} = \alpha + \beta_1 R_{mt} + \beta_2 R_{MSCI,t} + \beta_3 R_{US,t} + e_{it}$

Where $R_{i,t}$ and $R_{m,t}$ are the weekly return of the individual stock and the local market index (Argentina: MERVAL, Brazil: IBOVESPA, Chile: IPSA, Colombia: COLCAP, Mexico: MexIPC, Peru: IGBVL). $R_{ind,t}$ is the weekly industry return according to the One-Digit SIC code. $R_{MSCI,t}$ is the weekly MSCI Latin American Index return. $R_{US,t}$ is the weekly SP-500 Index return. We run the model regression using MSCI Latin American Index and SP-500 Index return to control for systematic shocks associated with the region (MSCI Latin American) and systematic shocks affected by the most important financial market associated with Latin America (SP-500). According to Chan and Hameed (2006) including industry returns as an additional factor is problematic because in some financial markets the economy is dominated by a few industries making it difficult to separate industry from market effects. For that reason, we test our hypothesis using the augmented market with and without the industry portfolio returns.

It is important to highlight that the literature uses the market model to obtain the stock return synchronicity (R^2) of a stock using the returns of a market, industry or external markets ((Morck,Yeung, and Yu (2000, Jin and Myers (2006), Dang et al. (2015) and Chan and Hameed (2006)). In this paper we are interested in error term ($\hat{e}_{i,t} = R_{it} - \hat{R}_{it}$) to calculate the stock return excess comovement. We calculate $\hat{e}_{i,t}$ using the weekly returns denominated in local currency and US dollars. Mink (2015) shows that calculating the correlation in US dollars might bias the results in cases where emerging countries are affected by the same external shocks (financial crisis, commodities shock, etc.) increasing the exchange rates correlation. Then, using returns denominated in US dollars might not accurately reflect price fluctuations in fundamentals since returns converted into a common currency also reflect fluctuations in the exchange rate.

In addition, the objective of using idiosyncratic returns is that excess correlation generated by the analyst coverage network should be reflected in the error term of the above regression. Following Israelsen (2014), our main measure for excess comovement is:

$$y_{p.t} = \frac{\sum_{t=1}^{N} \hat{e}_{i,t}\hat{e}_{j,t}}{\sqrt{\sum_{t=1}^{N}(\hat{e}_{i,t})^2 \sum_{t=1}^{N}(\hat{e}_{j,t})^2}}$$

We require that each firm must have at least 24 valid weekly return observations in a given year to calculate the correlation based on idiosyncratic returns. Since, we use two models and the weekly returns are denominated in local currency and US dollars, we have four measures. Finally, the comovement (pairwise correlation) is calculated using raw returns in the domestic currency and US dollars.

2.4 Summary Statistics

Our final sample contains 256 Latin Americans firms from the period 2000-2014. Specifically, we only consider firms with analysts following them. Thus, our study has 27,833 (50,221) firm-pair-year observations within (across) countries.

Panel A of Table 2.1 provides the descriptive statistics for the ACN. Considering the across-country sample, approximately only 2,555 pair firms share at least one analyst (5% with respect to the subsample). However, for the pairs of firms with analysts in common the number of analysts is 1.58 on average. The main variables of our study $NumA$ and $RhoA$ are on average close to zero in the entire sample. But, conditional on having analysts in common those numbers jump to 0.1 for the case of $NumA$ and 0.22 when we consider the $RhoA$ statistics.

When we consider the firm-pair-year observations within countries the network is more dense. On average firms share 0.65 analysts considering the overall subsample. However, conditional on sharing at least one analyst, pairs of firms have on average 2.48 analysts in common. Also, the statistics for $NumA$ and $RhoA$ are much larger. When we consider the full sample, 9,871 pairs of firms have at least one analyst in common and the distribution is concentrated in the top quartile.

We also calculate the brokerage house coverage network for our sample. We identify pairs of stocks connected by one brokerage house when analysts working for that brokerage house make at least one earnings forecast during the year and the forecast is made at most six months before the end of the fiscal period and at least three months after the end of the fiscal period. The brokerage house network is more dense as compared to the analyst network. Within (across) countries a pair of stocks is connected by 2.7 (0.86) brokerage houses on average.

Panel B of Table 2.1 shows the summary statistic for the outcome variables (correlation based on raw returns and idiosyncratic returns). The raw correlations on average are larger than idiosyncratic correlations for both within- and across-country subsamples (also in the full sample). Those results are not surprising since idiosyncratic returns only capture firm-specific information without considering market-wide or industry information. Also, the market model helps us to tease out the systematic risks that affect each country, industry and the entire region. Moreover, the correlation based on idiosyncratic returns across countries is, on average, close to zero. Which is smaller as compared to the correlation within countries (2%-5%).

The raw correlations based on returns denominated in local currency and US dollars confirm the results of Mink (2015). Exchange rates can influence the results when currencies are highly correlated at certain period of times. The correlation based on weekly returns in local currencies (25% and 16% for the within- and across-country subsamples, respectively) are smaller as compared to correlation in US dollars (45% and 30% for the within- and across-country subsamples, respectively). The statistics considering the full sample present similar results as explained above.

2.5 Empirical Results

In this section we discuss our empirical results. The discussion is divided into five subsections. First, we provide evidence of stock return comovement within and across countries. In the next subsection we show the results regarding excess comovement and additional cross sectional tests. Then, we exploit the changes in MSCI Latin American index constituents to reduce the concern about the endogeneity problems of the network formation. In the following subsection, we display the results using the brokerage house coverage network. Finally, we show the importance of common coverage by calculating the stock return synchronicity among firms that are connected across countries.

2.5.1 Stock Return Comovement

In Table 2.2, we provide the results of estimating equation (3) using the full sample, pairs of stocks in the same country (within) and pairs of stocks in different countries (across). The dependent variable is pairwise correlation between firm i and j using weekly returns (raw) denominated in local currency and US dollars. Regarding our variables of interest, $NumA$ and $RhoA$ are positive and statistically different from zero for the the three cases (full sample, within and across countries). Moreover, the coefficient associated with $NumA$ is consistently larger than $RhoA$. In terms of economic magnitudes, when $NumA(RhoA)$ increases one standard deviation, the weekly return correlation (using local currency) rises by 1.54% (1.43%) when we consider the full sample (Columns (1)-(4)).[6] Moreover, using weekly returns denominated in US dollars the correlation increases by 1.15% (1.05%). According to Muslu et. al (2014) these results suggest the presence of significant *coverage-specific* spillovers throughout the year, given that the average raw pairwise correlation for the sample within countries using returns denominated in local currency (US dollars) is 19% (35%).

[6] $NumA$ (1.54%= 0.257 $\times$0.06). $RhoA$ (1.43%= 0.119 $\times$0.12).

In columns (5)-(6) we display the within-country results.[7] The coefficients associated with $NumA$ and $RhoA$ are significant and statistically different from zero in the two columns. In terms of economic magnitudes an increase in one standard deviation in the value of $NumA$ ($RhoA$) rises by 1.54% (1.56%) the stock return comovement.[8]

In columns (7)-(8) we show the effect of the analyst coverage network on pairs of stocks across countries. The coefficient associated with $NumA$ and $RhoA$ are positive and statistical different from zero as in previous results. The economic magnitude is 0.27% (0.25%) using weekly returns in US dollars, when the variable $NumA$($RhoA$) increases in one standard deviation. These results suggest that the analyst coverage network has a positive economic impact on comovement between pairs of stocks.

Finally, the control variables that affect the information flow between pairs of stocks such as ADR, MSCI, Number of Days traded and PZDR are statistically different from zero. For the case of ADR(MSCI) the results suggest that the raw correlation between a pair of stocks is higher when both firms are cross listed in an US stock exchange (members of the MSCI Latin American Index). Moreover, when pairs of firms have larger differences in liquidity (PZDR) or numbers of days traded the stock return correlation is lower. Regarding the variable *(CHO),* difference in the fraction of shares closely held by insiders and controlling shareholders do not affect the raw pairwise correlation in the within-country subsample, but it is an important determinant for the across-country subsample. Pairs of stocks across countries face more comovements when the difference in insider ownership is low.

2.5.2 Excess Comovement

In this subsection we display the results regarding excess comovement (pairwise correlation based on weekly idiosyncratic returns). As we explained in the methodology section we

[7]For brevity we display the results using weekly returns in local currency; the results are similar using US dollars.

[8] $NumA$ (1.54%= (0.192 $\times$0.08)). $RhoA$ (1.56%= 0.087 $\times$0.18).

calculate the Model 1 and Model 2 using weekly returns denominated in local currency and US dollars. Table 2.3 Panel A reports the coefficients estimated from equation (3) using the full sample. The coefficients associated with $NumA$ and $RhoA$ are positive and statistically significant. In fact, they are larger than the coefficients found for the stock return comovement. In addition, the results show that the coefficients are robust to different specifications in the way that we calculate excess comovement.

Regarding the economic magnitude, an increase in one standard deviation in the variable $NumA$($RhoA$) causes the excess comovement to rise by 1.75%= 0.292 ×0.06 (1.64%= 0.137 ×0.12). If we consider that the average excess comovement is 2% (using Model 1 and weekly returns in US dollars) the economic impact of analyst coverage network is important. These results suggest that the analyst coverage network affects the excess comovement more than comovement between a pair of firms.

Focusing on the within-country results in Panel B. Columns (1)-(4) provide similar coefficients as in Panel A (full sample). However, depending on the variable of interest ($NumA$ or $RhoA$) and the specification of the excess comovement the economic magnitude is on average 2%, which is slightly higher as compared to the full sample.

In panel C we can see that the effect of across-country shared coverage is also positive and significant (although for the model 1 the results are significant at a p-value of 10%). In terms of economic magnitude, one standard deviation increase in the variable $NumA$($RhoA$) raises the excess comovement between pairs of stocks across countries by 0.17% (0.16%). Even though the magnitude seems to be small the average excess comovement for pairs of stocks across countries is only 1% (using Model 1 and weekly returns in US dollars), then relative to the sample the impact of the analyst coverage is large.

Surprisingly, the coefficients associated with the dummy variables *pair ADR* and *pair MSCI* lose statistical significance for the cases of the full sample and within-country connections. Moreover, the coefficients have negative signs, contrary to the results regarding comovement in Table 2.2. However, for the case of across-country subsample, only the coefficients associated with *pair MSCI* are still positive and significant suggesting that the excess comovement is affected systematically for the MSCI Latin American Index membership.

Using the last results associated with the MSCI Latin American Index we perform additional cross-sectional tests exploiting the interaction between the dummy variable *pair MSCI* and our variables of interests ($NumA$ or $RhoA$). In the previous table we showed that excess comovement is higher if investors trade based on public (*coverage-specific* information) provided by shared coverage. Thus, we expect that the excess comovement should be higher for pairs of stocks with less friction to trade, because prices should reflect better the information available. In emerging financial markets the liquidity and foreign investability have important effects on market efficiency (Bae et al. (2012)). Then, we would like to test whether pairs of firms with less frictions to trade, more liquidity and higher level of foreign investability, face more excess comovement when they have analysts in common. To do so, we focus on firms with higher investability, which are the constituents of the MSCI Latin American Index. For being part of the index stocks have to be more liquid and with higher level of foreign investability. Combining the analyst coverage network and the ability to trade based on analyst information generated we expect that the excess comovement would be higher in cases where a pair of stocks, both firm i and j, are members of the MSCI Latin American Index.

In Table 2.4 we display the results for the across-country sample using the interaction terms $NumA\ X\ MSCI$ and $RhoA\ X\ MSCI$. In columns (1)-(4) we can see the coefficients associated with the variable $NumA\ X\ MSCI$. In the four columns the coefficient are positive and statistically different from zero suggesting that firms that are easier to be traded have higher excess comovement when they have more analysts in common. The coefficients range from 0.150 to 0.224 depending on the specification used to calculate idiosyncratic weekly returns. When the variable is $RhoA\ X\ MSCI$ the results are similar; the coefficients range from 0.146 to 0.217. These results confirm our hypothesis that investor can increase excess comovement for pairs of stocks across countries when they have analysts in common and the stocks are easy to trade.

Our next cross sectional test is related to the analyst heterogeneity. If the excess comovement associated with analyst coverage is driven by information, then differences in analyst characteristics such as quality, size of brokerage house, or domestic versus international status of analysts should receive different attention from investors (domestic versus foreign investors). In Table 2.5 we try to differentiate the effect of analyst coverage between international and domestic analysts. To do so, we create a proxy variable exploiting the asymmetry in coverage between analysts from developed markets (Wall Street) and emerging markets (Latin America). It is very unusual that analysts from Latin America follow firms in developed markets because they have access to reports from analysts in developed countries and usually Latin American brokerage houses or investment funds are clients of larger financial institutions in advanced markets. Hence, Latin American analysts and investors usually outsource the production of information about firms in developed countries. However, the opposite is not usually the case. Larger investment banks such as JP Morgan and Goldman Sachs hire analysts to follow firms in emerging countries in addition to firms in developed markets in order to provide information for their investors (foreign).

We exploit that asymmetry and we classify as domestic those analysts that only follow Latin American firms. On the other hand, we classify as international analysts those who follow Latin American firms but who also follow firms in the US.[9] Our proxy variable tries to capture that international analysts provided information to foreign investors that are more willing to trade stocks across countries, which increases excess comovement. Then, we argue that domestic analysts affect excess comovement for pairs of stocks within countries and international analysts affect the excess comovement of across-country pairs of stocks.

Our results in Table 2.5 partially support our hypothesis. Regarding pairs of stocks within countries (Columns (1)-(4)), domestic analysts have a larger effect on excess comovement as compared to domestic analysts. However, in unreported tests we find that the two coefficients are not statistically distinguishable. When we consider the across countries sample we do find difference between domestic and international analysts. The coefficients associated with the latter are positive and statistically different from zero ($NumA - International$ and $RhoA - International$), but the coefficients of the former are not statistically significant, although they are positive ($NumA - Domestic$ and $RhoA - Domestic$).

[9] We combine the I/B/E/S US-file and I/B/E/S Non US-file to identify the analysts that are in both files.

Also, the coefficients associated with international analysts are larger than domestic analysts. These results suggest that our proxy variable helps us to differentiate the effect on excess comovement depending on the type of analysts. The international ones affect pairs of stocks across countries more than domestic analysts. It is important to highlight that in unreported tests, we do not find that the coefficients of international analysts are statistically larger than domestic analysts (relative comparison). Although, we can say that the effect of international analysts is statistically different from zero, but that is not the case for domestic analysts. Hence, our results suggest that the major source of excess comovement between across-country pairs of stocks are the connections created by international analysts.

2.5.3 Dealing with Endogeneity Concerns

The main concern about the analyst coverage network is the endogeneity problems generated by unobservable characteristics of analysts and/or firms that might drive the excess comovement. For instance, analysts can choose a pool of firms in a particular industry or multiple industries with similar exposure to systematic risk. Hence, excess comovement between pairs of stocks in the analyst coverage could simply be capturing unmeasured systematic risk not accounted for by risk factors in the market model and control variables (selection on observables fails). We follow the methodology provided by Israelsen (2014) to show that additions to the MSCI Latin America Index have an impact on the shared coverage and excess comovement .[10]

The index captures large and mid cap representation across five emerging-market countries in Latin America (Brazil, Chile, Colombia, Mexico and Peru). With 119 constituents, the index covers approximately 85% of the free float-adjusted market capitalization.[11] In

[10]Israelsen (2014) uses monthly changes in the SP-500 constituents. Emerging market studies such as Kot et al. (2015) and Wang et al. (2015) provide evidence of the effects of index reconstitution for the cases of Seng and CSI 300 Indexes.

[11] MSCI defines the free float of a stock as the proportion of shares outstanding that is available for purchase by international investors. Moreover, after 2000 MSCI uses as main variable to be part of the index the free float of the stocks adjusted by the market capitalization of each security using a factor referred to as the foreign inclusion factor.

June and December (first day of the month) of each year Morgan Stanley Capital International Inc. (MSCI) performs a rebalancing of the Latin American index fund. However, the announcement date is two to three weeks before the effective date.[12] Thus, the price reaction (buyer/seller pressure) to the new composition is before June or December 1^{st}. MSCI can either change the weights of the index constituents or perform additions (deletions) of Latin American firms. The criteria for being part of the index are public.[13]

We use additions to the MSCI index as an exogenous shock in the analyst coverage and the ACN that affects excess comovement. Since the rebalancing in the MSCI index is driven by the free float and foreign investability, firms are unable to manipulate their incorporation to the index based on this variable (then firms can not attract analysts). Moreover, when firms are incorporated to the index they suffer buying pressure from investment funds and institutional investors. And new firms in the index become more attractive to investors and they capture the attention of analysts, because more investors will demand information about those firms. Also, previous literature shows that analysts follow stocks that are more likely to reflect the information generated by them on prices (Bushman et al. (2005)). Thus, firms that belong to the index are more liquid and easy to trade, which increases the interest of analysts to start following them.

Below, we present anecdotal evidence from a news report regarding the buying pressure reaction from passive funds when MSCI announced the addition of a Mexican firm to the MSCI Colombia Index.

"Cemex Latam Holdings SA, a cement maker in Central and South America, rose the most on record after MSCI Inc. included the company in a gauge tracked by investment funds. The shares advanced 3.8 percent to 13,280 pesos at 11:41 a.m. in Bogota after earlier gaining 5.3 percent, the biggest intraday increase since the company's Monterrey, Mexico-based parent, Cemex SAB, sold the shares in November in an initial public offering. Bogota-based Cemex Latam was added to MSCI's Colombia index as part of a rebalancing

[12]For instance, the announcement dates for the semi-annual index reviews in 2016 are May 12 and November 14. https://www.msci.com/eqb/pressreleases/archive/ir_dates.pdf

[13]Hau et al. (2010) offer a detailed institutional background of the MSCI and its index maintenance.

announced yesterday, with changes due to take effect June 3. The addition was one of the "biggest surprises," Banco Santander SA analysts Stefano Rizzi and Jesus Gomez wrote in an e-mailed report yesterday. Cemex Latam is one of three stocks for which "we expect the largest buying pressure from passive funds," they wrote. The rebalancing may create "buying pressure" on Cemex Latam equivalent to 8.6 days of average trading volume, according to the report. " Bloomberg News. May 16, 2013

Another important characteristic of the MSCI rebalancing methodology is the semi-annual reviews. Contrary to the S&P 500, which is reviewed infrequently and with no explicit methodology for the index composition rebalancing, the MSCI Latin American Index has only two review periods in each year.[14] Hence, we can mitigate the concerns associated with excess comovement due to buying/selling pressures caused by passive investment funds that try to replicate the index. Also, when we calculate the idiosyncratic returns using the MSCI index returns as an additional risk factor (Model 1 and 2) we try to mitigate (at least partially) the effect of investment funds demand for those firms added to the index.

In Panel A of Table 2.6 we provide the results regarding changes in analyst coverage and analyst coverage network before and after additions to the MSCI Latin America Index. We identify additions to the MSCI Latin American Index for the sample period 2001-2014 tracking the changes in the index constituents using Bloomberg. Through quarterly observations and the I/B/E/S Summary File we perform a mean tests on the changes in the number of analysts following firms added to the index. Our results show that there is an increase in the number of analysts following a firm after it is added to the index. However, the increase in coverage takes time, at least four quarters after the MSCI reviews. After one year, there is at least one new analyst following the firms incorporated to the index. In addition, our variables that measure the shared coverage ($NumA$ and $RhoA$) show an increase in the following two years after the index reviews. The difference in shared coverage between the calendar year before and after is 0.0158 (0.297) for the variable $NumA$ ($RhoA$),

[14] Previous papers track the index reviews checking the index constituents on a monthly basis.

also the mean test show that the differences are statistically distinguishable. Moreover, we show that the average variable $NumA$ ($RhoA$) is statistically larger after the MSCI additions. These results are also consistent with those provided by Israelsen (2014).

We normalize our analysis using as $t = 0$ the calendar year in which the firm was added to the index. We use the previous ($t = -1$) and the next calendar year ($t = +1$) to calculate the changes in excess comovement due to the additions of firms into the MSCI Latin American Index. Also, our subsample contains all the pairs of firms affected by the addition to the index by at least one firm of the pair (i or j). And we keep only pairs of firms that are not affected by any other MSCI review in the year after ($t = +1$). Finally, we require that the pairs of firms have at least one analyst in common prior to the MCSI reviews.

Panel B presents the results regarding the effect of changes in analyst coverage network on excess comovement after the MSCI additions. Our variables of interest are $\Delta NumA$ *(-1 vs.+1)* and $\Delta RhoA$ *(-1 vs.+1)*, which represent the changes in the ACN before and after the MSCI reviews. We find that after the index rebalancing the pairs of stocks suffer an increase in the excess comovement caused by an increase in the analysts in common between them. The coefficient associated with $\Delta NumA$ *(-1 vs.+1)* and $\Delta RhoA$ *(-1 vs.+1)* range from 0.24 to 0.37 and 0.13 to 0.19, respectively. The results are robust to different specifications in terms of weekly returns (local currency vs. US dollars) and the market model used to calculate the idiosyncratic returns. Also, we control for country-pair and year fixed effects and changes in the absolute difference of the control variables explained above. Overall, we show that exogenous changes in the MSCI membership increase the analyst coverage of firms added to the index affecting, at the same time, the number of analysts in common for pairs of stocks. Thus, this change in the shared coverage increases the excess comovement between pairs of stocks.

2.5.4 Brokerage Coverage Network: Comovement and Excess Comovement

According to our summary statistics the analyst coverage network is sparse, especially for the pairs of stocks in the across-country subsample. However, if we identify shared coverage at brokerage level we can obtain a more dense network. Creating the brokerage coverage network (BCN) is also important because if analysts work for the same brokerage house they might have a similar methodology to acquire, process, generate and disseminate the information. Hence, we expect that their forecast errors are also correlated. Additionally, under the market segmentation hypothesis (Grullon et al. (2014)) investment banks and their brokerage houses have a defined pool of clients who trade based on the information that they provide. Hence, firms connected by brokerage house should also suffer return comovement and excess comovement. However, under the hypothesis that analyst coverage provides *coverage-specific* information useful for investors the effect of the analyst coverage network should be higher than the brokerage coverage network on comovement and excess comovement.

In addition, one advantage of using the common brokerage variables is that they also provide additional power in explaining comovement and excess comovement. Since BCN is more dense than the ACN we can reduce concerns about the explanatory power of the analyst coverage network (sparse), especially for the across-country subsample. The second advantage is related to the endogeneity issues in analyst network formation. Since brokerage houses have analysts following a larger pool of firms rather than firms selected by individual analysts any comovement and excess comovement explained by the common brokerage house is more likely to be driven by the *coverage-specific information* hypothesis rather than omitted variables associated with analysts' characteristics that affect the decision to cover a particular stock.

To test our hypothesis we run the regression of equation (3), replacing the analyst coverage network variables ($NumA$ and $RhoA$) with the brokerage coverage network measures ($NumB$ and $RhoB$). In Table 2.7 we display the results using the stock return comovement (raw correlation). The coefficients associated with $NumB$ and $RhoB$ are all positive and significant, ranging from 0.018 to 0.089 depending on the sample used (full, within or across countries). However, those coefficients are much smaller than those found in Table 2.2 with respect to each sample. Finally, Table 2.8 reports the results using excess comovement as a dependent variable. The coefficients are positive and statistically different from zero for the full sample and the within-country subsample. Unfortunately, we do not find robust results for the across-country subsample. Again, the coefficients are smaller than those found in Table 2.3.

2.5.5 Across-Country Connections and Stock Return Synchronicity

We perform a final test to reduce concerns regarding across-country results. Following Muslu et al. (2014) we calculate the increase in stock return synchronicity when an individual firm is connected to other firms across countries by the same analysts. Under the *coverage-specific information* hypothesis, if firms are connected the analyst information should be reflected in stock return synchronicity. Peer firms' returns should be able to explain individual firm's returns.

To test this, we generate a new independent and dependent variable. We calculate the degree of individual firms with respect to the across-country connections ($International-Degree$). In social network terminology the number of connections is called $Degree$, which is one of the most important centrality measures.[15] If analysts play an important role connecting firms through the information channel we should expect that individual firms with a larger number of connections (higher degree) should have higher stock return synchronicity with respect to a portfolio return based on the firms to which an individual firm is connected.

In order to construct our dependent variable we run the following two augmented market model regressions using weekly returns denominated in US dollars to calculate the R^2 for

[15] See Matthew (2010) for an overview about the centrality measures.

firm i.

(S1): $R_{it} = \alpha + \beta_1 R_{mt} + \beta_2 R_{ind,t} + \beta_3 R_{MSCI,t} + \beta_4 R_{US,t} + \beta_5 R_{ACN-DOM,t} + e_{it}$

(S2): $R_{it} = \alpha + \beta_1 R_{mt} + \beta_2 R_{ind,t} + \beta_3 R_{MSCI,t} + \beta_4 R_{US,t} + \beta_5 R_{ACN-DOM,t} + \beta_6 R_{ACN-INT,t} + e_{it}$

S1 and S2 are based on Model 1 as explained in the methodology section, where $R_{ACN-DOM,t}$ is the returns of an equally-weighted portfolio of the stocks with shared coverage in the same country (domestic) as the firm i.[16] Moreover, $R_{ACN-INT,t}$ is the returns of an equally-weighted portfolio of the stocks with shared coverage in different countries (International) with respect to the firm i. After calculating the R^2 for both regressions (R^2_{S1} and R^2_{S2}) we calculate our dependent variable $\Delta SyncR^2$ (Muslu et al. (2014), Piotroski and Roulstone (2004) and Chan and Hameed (2006)).

$$\Delta SyncR^2 = Log(\frac{R^2_{S2}}{1 - R^2_{S2}}) - Log(\frac{R^2_{S1}}{1 - R^2_{S1}})$$

Our measure $\Delta SyncR^2$ isolates the ability of the shared coverage portfolio to explain the variability of stock returns. Hence, we should expect that firms with larger *International Degree* have greater stock return synchronicity with respect to peer firm portfolio returns (across countries). Then the equation to regress is the following:

$$\Delta SyncR^2_{it} = \alpha + \beta_1 International\ Degree_{it} + \gamma X_{it} + \delta_{ct} + \lambda_k + \epsilon_{it} \tag{2.2}$$

We include country-year F.E (δ_{ct}) and industry F.E (λ_k) to control for time-varying country characteristics and industry characteristics constant over the time, respectively. Moreover, the matrix X_{it} has a battery of control variables.

Table 2.9 displays the results using Model 1 and Model 2 explained in the methodology section plus the $R_{ACN-DOM,t}$ and $R_{ACN-INT,t}$ to calculate $\Delta SyncR^2$. Columns (1)-(2) and (5)-(6) show the effect of $Coverage_{it}$ (number of analysts following the firm i) on our dependent variable. The coefficients are positive and statistically significant. These results

[16] We also run the regression using the Model 2.

are consistent with results provided by Muslu et al (2014), Piotroski and Roulstone (2004) and Chan and Hameed (2006). Coverage intensive firms produce more public information and have higher level of stock return synchronicity. However, the most important result is that after controlling for our main independent variables, $International\ Degree_{it}$, the coefficients associated with $Coverage_{it}$ lose explanatory power and most are no longer statistically different from zero. In fact, $International\ Degree_{it}$ variable becomes more important with a positive and statistically significant effect on $\Delta SyncR^2$. These results are consistent with the hypothesis that peer firms connected by common coverage are able to explain stock return variability of an individual firms (the marginal increase in stock price synchronicity ($\Delta SyncR^2$)).

As in Muslu et al. (2014), this evidence suggests that the explanatory power of $Coverage_{it}$ is subsumed by $International\ Degree_{it}$. More importantly, stock returns of firms in different countries increase the stock return synchronicity of individual firms even after controlling for domestic and international index returns, industry returns and domestic peer firm portfolio returns. Overall, individual firm's weekly returns comove more strongly with weekly returns of other stocks connected by across-country shared coverage.

2.6 Conclusion

In this paper we test the *Coverage-Specific Information Spillover Hypothesis* for a sample of Latin American firms. Using a comprehensive set of stocks between years 2000 and 2014, we provide evidence that analyst coverage network is an additional source of comovement and excess comovement for pairs of stocks within and across countries.

Using analysts as an important source of information, correlation between pairs of firms reflects common information generated by shared coverage. As a result, the return comovement between stocks is higher and economically important. In addition, we provide cross-sectional tests regarding the heterogeneity of analysts (international vs domestic) and stock characteristics. Analysts who work in developed countries and follow firms in Latin America are the source of excess comovement for the case of across-country pairs of stocks. Also, firms that are easy to trade for domestic and foreign investors face more excess comovement.

Moreover, we provide robustness tests exploiting the MSCI Latin American Index reviews of its constituents to reduce the concerns of the endogeneity issues in the network formation. Also, we create the brokerage coverage network to test whether brokerage houses have an effect on return correlations. We find, that brokerage houses also matter to explain comovement and excess comovement in pairs of stocks.

Finally, this study contributes to the literature of emerging markets by providing evidence about the information role of analysts and how they are key players in connecting firms through their shared coverage (information channel). Moreover, we go further by showing that comovement and excess comovement at pair of firms-level. Previous studies use, mainly, indexes and aggregated data. Lastly, this paper contributes to the growing literature of networks as an important determinant in explaining financial contagion, commonalities and corporate policies. Specifically, our network based on common coverage is an important dimension in which firms are connected. For that reason, this paper helps to understand how connections between them make firms affect each other.

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2.8 Appendix B : Variable Definitions

- ADR: Dummy that takes the value of one when a firm is cross-listed on a U.S.exchange. $Pair\ ADR$ dummy that takes the value of one when both firm i and j is cross-listed on a U.S.exchange. *(Worldscope)*

- $AnnRet$: Annual stock returns. *(Datastream)*

- CHO: Closely held ownership. Fraction of shares closely held by insiders and controlling shareholders. *(Worldscope)*

- EPS: Earnings per share. Net income divided by number of outstanding shares. *(Worldscope).*

- $International - Degree$*:* Number of across-country connections that a firm has. We defined connection based in common coverage.

- $Leverage$: Ratio of the sum of total long-term debt plus total debt in current liabilities scaled by the market value of assets. *(Worldscope)*

- $Log(MKTCAP)$: Log of market capitalization. *(Worldscope)*

- $Log(Sales)$: Natural logarithmic of sales*. (Worldscope)*

- MTB: Market to Book ratio. Ratio of the sum of the total book value of debt plus market value of equity divided by book value of total assets. *(Worldscope)*

- $MSCI$: Dummy that takes the value of one when a firm is member of the MSCI Latin American index. $Pair\ MSCI$ dummy that takes the value of one when both firm i and j are members of the MSCI Latin American index. *(Bloomberg)*

- $NDays$: Number of days that the stock has been traded. *(Datastream)*

- $NumA(NumB)$: Number of analysts (brokerage houses) in common between pair of firms i and j divided by the total number of analysts (brokerage houses) covering either stocks in the pair (Muslu. et al, (2014)). *(I/B/E/S)*

- $PZDR$: Percentage of days that the stock had zero return. *(Datastream)*

- $RhoA(RhoB)$: $RhoA_{p,t} = \frac{N_p}{\sqrt{N_i N_j}}$.Number of analysts (brokerage houses) in common between pair of firms i and j divided by squared root of the total number of analysts (brokerage houses) covering either stocks in the pair (Israelsen (2014)).

- ROA: Return on Assets. Net income divided by total assets. *(Worldscope)*

- ROE: Return on Equity. Net income divided by total equity. *(Worldscope)*

- *Stock Price:* Stock price in U.S.dollars. *(Worldscope)*

- $Tangibility$: Ratio of the book value of Net Property Plant and Equipment divided by book value of total assets. *(Worldscope)*

- $Volatility$: Daily stock return volatility (annually calculated). *(Datastream)*

2.9 Tables

Table 2.1: Summary Statistics

This table presents the descriptive statistics for the analyst coverage network and the variables used in the regressions analysis. Panel A shows the characteristics of analyst networks in terms of number of analysts in common between pairs of firms. Panel B and C show the statistics for the outcome variables and control variables at firm-pair and individual firm level, respectively. All variables used in the regression analysis are winsorized at the 1st and 99th percentile.

Panel A: Pair Firms-Level																		
	Full Sample						Within-Country						Across-Country					
Analyst Coverage Network	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75
N Analysts in Common	78054	0.28	1.14	0	0	0	27833	0.65	1.76	0	0	1	50221	0.08	0.46	0	0	0
$NumA$	78054	0.02	0.06	0	0	0	27833	0.04	0.08	0	0	0.04	50221	0	0.03	0	0	0
$RhoA$	78054	0.04	0.12	0	0	0	27833	0.08	0.18	0	0	0.07	50221	0.01	0.06	0	0	0
N Analysts in Common>0	9871	2.25	2.44	1	1	2	7316	2.48	2.68	1	1	3	2555	1.58	1.32	1	1	2
$NumA > 0$	9871	0.13	0.1	0.06	0.09	0.17	7316	0.14	0.11	0.06	0.1	0.2	2555	0.1	0.07	0.05	0.07	0.12
$RhoA > 0$	9871	0.28	0.21	0.13	0.21	0.39	7316	0.31	0.22	0.13	0.24	0.43	2555	0.22	0.14	0.12	0.17	0.27
N Analysts in Common-Inter.	78054	0.09	0.49	0	0	0	27833	0.19	0.73	0	0	0	50221	0.04	0.27	0	0	0
N Analysts in Common-Dom.	78054	0.19	0.89	0	0	0	27833	0.46	1.39	0	0	0	50221	0.04	0.31	0	0	0
$NumA - International$	78054	0.02	0.11	0	0	0	27833	0.04	0.16	0	0	0	50221	0.01	0.06	0	0	0
$NumA - Domestic$	78054	0.04	0.18	0	0	0	27833	0.11	0.28	0	0	0	50221	0.01	0.07	0	0	0
$RhoA - International$	78054	0.01	0.06	0	0	0	27833	0.02	0.08	0	0	0	50221	0	0.03	0	0	0
$RhoA - Domestic$	78054	0.02	0.1	0	0	0	27833	0.06	0.14	0	0	0	50221	0.01	0.04	0	0	0
N Analysts in Common-Inter. >0	4321	1.66	1.32	1	1	2	2982	1.77	1.47	1	1	2	1339	1.41	0.87	1	1	1
N Analysts in Common-Dom.>0	7463	2.01	2.15	1	1	2	5943	2.16	2.32	1	1	2	1520	1.42	1.09	1	1	1
$NumA - International > 0$	4321	0.38	0.26	0.22	0.28	0.45	2982	0.41	0.28	0.22	0.29	0.49	1339	0.33	0.18	0.22	0.26	0.38
$NumA - Domestic > 0$	7463	0.46	0.39	0.23	0.32	0.52	5943	0.5	0.42	0.23	0.33	0.58	1520	0.35	0.2	0.22	0.27	0.41
$RhoA - International > 0$	4321	0.2	0.14	0.11	0.16	0.26	2982	0.21	0.15	0.11	0.17	0.28	1339	0.18	0.11	0.11	0.14	0.22
$RhoA - Domestic > 0$	7463	0.26	0.19	0.11	0.19	0.35	5943	0.27	0.2	0.12	0.2	0.38	1520	0.21	0.15	0.11	0.17	0.25
Brokerage Coverage Network																		
N Brokerages in Common	78054	1.51	2.2	0	1	2	27833	2.7	2.8	1	2	4	50221	0.86	1.42	0	0	1
N Brokerages in Common>0	42963	2.75	2.33	1	2	4	21466	3.5	2.71	1	3	5	21497	2.01	1.55	1	1	2
$NumB$	78054	0.09	0.11	0	0.07	0.17	27833	0.16	0.12	0.06	0.16	0.25	50221	0.06	0.08	0	0	0.11
$RhoB$	78054	0.21	0.23	0	0.17	0.37	27833	0.34	0.24	0.16	0.36	0.53	50221	0.13	0.17	0	0	0.25
$NumB > 0$	42963	0.22	0.15	0.11	0.18	0.3	21466	0.21	0.1	0.13	0.2	0.27	21497	0.14	0.07	0.08	0.12	0.17
$RhoB > 0$	42963	0.37	0.18	0.24	0.35	0.5	21466	0.45	0.18	0.31	0.44	0.57	21497	0.3	0.14	0.2	0.28	0.38

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Panel B: Pair Firms-Level																		
Outcome Variables	Full Sample						Within-Country						Across-Country					
Comovement	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75
Raw Correlation (Local)	78054	0.19	0.18	0.07	0.19	0.31	27833	0.25	0.19	0.12	0.25	0.37	50221	0.16	0.17	0.04	0.16	0.28
Raw Correlation (USD)	78054	0.35	0.2	0.21	0.35	0.49	27833	0.45	0.18	0.33	0.46	0.57	50221	0.3	0.19	0.17	0.3	0.43
Excess Comovement																		
Model 1 Correlation (Local)	78054	0.02	0.16	-0.09	0.02	0.13	27833	0.04	0.18	-0.08	0.04	0.16	50221	0.01	0.15	-0.1	0	0.11
Model 2 Correlation (Local)	78054	0.01	0.16	-0.1	0.01	0.11	27833	0.02	0.17	-0.1	0.02	0.14	50221	0	0.15	-0.11	0	0.1
Model 1 Correlation (USD)	78054	0.02	0.17	-0.09	0.02	0.13	27833	0.05	0.18	-0.07	0.05	0.17	50221	0.01	0.16	-0.1	0.01	0.11
Model 2 Correlation (USD)	78054	0.01	0.16	-0.1	0.01	0.12	27833	0.03	0.17	-0.09	0.03	0.15	50221	0	0.15	-0.11	0	0.1
Control Variables																		
Pair ADR	78054	0.16	0.37	0	0	0	27833	0.16	0.36	0	0	0	50221	0.16	0.37	0	0	0
Pair MSCI	78054	0.22	0.41	0	0	0	27833	0.25	0.43	0	0	0	50221	0.2	0.4	0	0	0
Absolute difference																		
CHO	78054	0.26	0.19	0.1	0.22	0.38	27833	0.26	0.19	0.1	0.22	0.38	50221	0.26	0.2	0.1	0.22	0.39
Leverage	78054	0.23	0.17	0.09	0.19	0.33	27833	0.23	0.17	0.09	0.19	0.33	50221	0.23	0.17	0.09	0.19	0.33
Log(Sales)	78054	1.5	1.2	0.59	1.26	2.13	27833	1.53	1.21	0.61	1.29	2.16	50221	1.49	1.2	0.58	1.24	2.11
MTB	78054	0.82	1.05	0.2	0.49	0.99	27833	0.87	1.12	0.2	0.49	1.02	50221	0.8	1	0.2	0.49	0.97
Log(MKTCAP)	78054	1.55	1.18	0.63	1.3	2.24	27833	1.54	1.17	0.62	1.28	2.22	50221	1.56	1.18	0.63	1.31	2.25
ROE	78054	0.22	0.32	0.05	0.12	0.23	27833	0.23	0.33	0.05	0.12	0.25	50221	0.21	0.32	0.05	0.11	0.22
ROA	78054	0.07	0.08	0.02	0.05	0.1	27833	0.08	0.08	0.02	0.05	0.1	50221	0.07	0.08	0.02	0.05	0.1
EPS	78054	0.74	0.93	0.15	0.4	0.93	27833	0.85	1.03	0.17	0.47	1.1	50221	0.68	0.87	0.13	0.36	0.84
Stock Price	78054	7.68	9.64	1.75	4.51	9.96	27833	7.5	9.75	1.67	4.32	9.65	50221	7.77	9.57	1.79	4.63	10.13
AnnRet	78054	0.45	0.52	0.14	0.3	0.56	27833	0.44	0.52	0.13	0.29	0.53	50221	0.46	0.52	0.14	0.31	0.57
Volatility	78054	0.01	0.01	0	0.01	0.01	27833	0.01	0.01	0	0	0.01	50221	0.01	0.01	0	0.01	0.01
Ndays	78054	16.34	35.31	0	5	11	27833	10.3	31.15	0	0	2	50221	19.69	36.99	5	6	12
PZDR	78054	0.11	0.16	0.02	0.05	0.12	27833	0.08	0.14	0.01	0.03	0.07	50221	0.13	0.17	0.03	0.07	0.14

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Panel C: Firm-Level						
	N	Mean	SD	P25	Median	P75
Model 1: Aug. R^2	2169	0.04	0.08	0	0.01	0.05
Model 2: Aug. R^2	2169	0.04	0.08	0	0.01	0.05
$InternationalDegree$	2169	5.62	6.6	0	4	8
Coverage	2169	6.87	5.62	2	5	10
ADR	2169	0.41	0.49	0	0	1
MSCI	2169	0.46	0.5	0	0	1
Closely held ownership (*CHO*)	1398	0.53	0.23	0.38	0.56	0.7
Log(Sales)	2169	20.89	1.48	19.94	20.95	21.85
MTB	2169	1.54	0.96	0.99	1.26	1.77
Leverage	2169	0.31	0.22	0.13	0.27	0.45
Tangibility	2169	0.41	0.24	0.21	0.42	0.61
ROA	2169	0.05	0.08	0.02	0.05	0.08
ROE	2169	0.1	0.27	0.04	0.1	0.19
Volatility	2169	0.02	0.01	0.02	0.02	0.03
N days Traded (*NDays*)	2169	223.74	39.03	227	238	241
Percentage zero days return (*PZDR*)	2169	0.22	0.21	0.09	0.13	0.23

Table 2.2: ACN and Comovement

The table presents the results of the effect of ACN on stock return comovement (raw pairwise correlation). On the top of each column appears the currency in which the returns are calculated. The variables *NumA* and *RhoA* measure the shared coverage between firm i and j (Muslu et al. (2014) and Israelsen (2014)). The control variables are winsorized at the 1st and 99th percentile. All regressions include industry-pair-year and country-pair-year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	Full Sample				Within Countries		Across Countries	
	Local Currency	US Currency	Local Currency	US Currency	Local Currency		US Currency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumA	.257	.192			.192		.089	
	(.019)***	(.016)***			(.025)***		(.028)***	
RhoA			.119	.088		.087		.041
			(.009)***	(.007)***		(.012)***		(.013)***
Pair ADR	.015	.012	.015	.012	.017	.017	.014	.014
	(.002)***	(.002)***	(.002)***	(.002)***	(.004)***	(.005)***	(.002)***	(.002)***
Pair MSCI	.026	.024	.026	.025	.032	.032	.023	.023
	(.002)***	(.002)***	(.002)***	(.002)***	(.004)***	(.004)***	(.002)***	(.002)***
Abs. Diff. CHO	-.007	-.009	-.007	-.009	-.010	-.010	-.009	-.009
	(.003)**	(.003)***	(.003)**	(.003)***	(.007)	(.007)	(.004)**	(.004)**
Abs. Diff. Leverage	.003	-.004	.003	-.004	-.008	-.008	.008	.008
	(.004)	(.003)	(.004)	(.003)	(.008)	(.008)	(.004)*	(.004)*
Abs. Diff. Log(Sales)	-.0005	-.001	-.0005	-.001	-.002	-.002	.0002	.0002
	(.0006)	(.0006)**	(.0006)	(.0006)**	(.001)	(.001)	(.0007)	(.0007)
Abs. Diff. MTB	-.003	-.001	-.003	-.001	-.002	-.002	-.002	-.002
	(.0008)***	(.0007)*	(.0008)***	(.0007)*	(.001)	(.001)	(.0009)**	(.0009)**
Abs. Diff. Log(MKCAP)	-.00004	.0008	-.0001	.0007	-.002	-.003	.002	.002
	(.0007)	(.0006)	(.0007)	(.0006)	(.001)*	(.001)*	(.0008)**	(.0008)**
Abs. Diff. ROE	.008	-.004	.008	-.004	.006	.006	.008	.008
	(.003)***	(.003)	(.003)***	(.003)	(.006)	(.006)	(.004)**	(.004)**
Abs. Diff. ROA	-.149	-.157	-.149	-.157	-.215	-.215	-.183	-.183
	(.014)***	(.013)***	(.014)***	(.013)***	(.028)***	(.028)***	(.017)***	(.017)***
Abs. Diff. EPS	-.00005	-.0007	-.00007	-.0007	-.0003	-.0003	-.003	-.003
	(.001)	(.0009)	(.001)	(.0009)	(.002)	(.002)	(.001)**	(.001)**
Abs. Diff. Stock Price	.0002	.0007	.0002	.0007	.0006	.0006	.0007	.0007
	(.0001)***	(.00008)***	(.0001)**	(.00008)***	(.0002)***	(.0002)***	(.0001)***	(.0001)***
Abs. Diff. AnnRet	-.031	-.038	-.031	-.038	-.042	-.042	-.035	-.035
	(.002)***	(.001)***	(.002)***	(.001)***	(.003)***	(.003)***	(.002)***	(.002)***
Abs. Diff. Volatility	-.073	-.736	-.076	-.738	.262	.255	-.731	-.731
	(.089)	(.082)***	(.089)	(.082)***	(.163)	(.163)	(.106)***	(.106)***
Number of Days	-.0003	-.0003	-.0003	-.0003	-.0004	-.0004	-.0003	-.0003
	(.00004)***	(.00004)***	(.00004)***	(.00004)***	(.0001)***	(.0001)***	(.00004)***	(.00004)***
Abs. Diff. PZDR	-.134	-.115	-.134	-.115	-.245	-.247	-.097	-.098
	(.009)***	(.008)***	(.009)***	(.008)***	(.026)***	(.026)***	(.009)***	(.009)***
Const.	.222	.321	.222	.321	.443	.458	.236	.236
	(.022)***	(.022)***	(.022)***	(.022)***	(.017)***	(.017)***	(.014)***	(.014)***
Obs.	78054	78054	78054	78054	27833	27833	50221	50221
R^2	.515	.675	.515	.675	.599	.599	.665	.665

Table 2.3: ACN and Excess Comovement

The table presents the results of the effect of ACN on stock excess comovement (pairwise correlation based on idiosyncratic returns). On the top of each column appears the currency in which the returns are calculated and the model used to obtain the idiosyncratic returns. The variables *NumA* and *RhoA* measure the shared coverage between firm *i* and *j* (Muslu et al. (2014) and Israelsen (2014)). The control variables are winsorized at the 1st and 99th percentile. All regressions include industry-pair-year and country-pair-year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Full Sample								
	Local Currency		US Currency		Local Currency		US Currency	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumA	.290	.276	.292	.280				
	(.023)***	(.023)***	(.022)***	(.023)***				
RhoA					.135	.128	.137	.131
					(.011)***	(.011)***	(.011)***	(.011)***
Pair ADR	-.002	.002	-.005	.0005	-.002	.002	-.005	.0007
	(.002)	(.002)	(.002)**	(.002)	(.002)	(.002)	(.002)**	(.002)
Pair MSCI	-.004	.0009	-.007	-.0003	-.003	.001	-.006	-.00009
	(.002)*	(.002)	(.002)***	(.002)	(.002)	(.002)	(.002)***	(.002)
Abs. Diff. CHO	-.003	-.003	-.005	-.006	-.003	-.003	-.005	-.006
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Abs. Diff. Leverage	.006	.004	.006	.003	.006	.003	.006	.003
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Abs. Diff. Log(Sales)	-.004	-.003	-.005	-.004	-.004	-.003	-.006	-.004
	(.0007)***	(.0007)***	(.0007)***	(.0007)***	(.0007)***	(.0007)***	(.0007)***	(.0007)***
Abs. Diff. MTB	-.002	-.002	-.001	-.001	-.002	-.002	-.001	-.001
	(.0009)*	(.0009)*	(.0009)	(.0009)	(.0009)*	(.0009)*	(.0009)	(.0009)
Abs. Diff. Log(MKTCAP)	-.005	-.003	-.004	-.002	-.005	-.003	-.004	-.002
	(.0008)***	(.0008)***	(.0008)***	(.0008)**	(.0008)***	(.0008)***	(.0008)***	(.0008)**
Abs. Diff. ROE	-.012	-.009	-.016	-.012	-.012	-.009	-.015	-.012
	(.003)***	(.003)***	(.003)***	(.003)***	(.003)***	(.003)***	(.003)***	(.003)***
Abs. Diff. ROA	.052	.032	.048	.036	.053	.032	.048	.036
	(.015)***	(.015)**	(.015)***	(.015)**	(.015)***	(.015)**	(.015)***	(.015)**
Abs. Diff. EPS	-.0009	-.001	-.0008	-.001	-.001	-.001	-.0008	-.001
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Abs. Diff. Stock Price	.0001	.00006	.0002	.00007	.0001	.00006	.0002	.00007
	(.0001)	(.0001)	(.0001)*	(.0001)	(.0001)	(.0001)	(.0001)*	(.0001)
Abs. Diff. AnnRet	-.006	-.007	-.006	-.006	-.006	-.007	-.006	-.006
	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***	(.002)***
Abs. Diff. Volatility	.010	-.066	-.087	-.163	.006	-.069	-.091	-.166
	(.098)	(.097)	(.098)	(.097)*	(.098)	(.097)	(.098)	(.097)*
NDays	-.00008	-.00006	-.0001	-.00004	-.00008	-.00006	-.0001	-.00004
	(.00004)*	(.00004)	(.00004)**	(.00004)	(.00004)*	(.00004)	(.00004)**	(.00004)
Abs. Diff. PZDR	.022	.015	.034	.014	.022	.015	.034	.014
	(.009)**	(.009)*	(.009)***	(.009)	(.009)**	(.009)	(.009)***	(.009)
Const.	.018	.035	.033	.036	.018	.035	.034	.036
	(.018)	(.019)*	(.021)	(.019)*	(.018)	(.019)*	(.021)	(.019)*
Obs.	78054	78054	78054	78054	78054	78054	78054	78054
R^2	.212	.184	.224	.19	.212	.183	.224	.19

Panel B: Within Countries

	Local Currency			
	Model 1	Model 2	Model 1	Model 2
	(1)	(2)	(3)	(4)
NumA	.239	.227		
	(.030)***	(.031)***		
RhoA			.111	.104
			(.014)***	(.014)***
Pair ADR	-.014	-.008	-.014	-.007
	(.005)***	(.005)	(.005)**	(.005)
Pair MSCI	-.012	-.005	-.011	-.005
	(.004)***	(.004)	(.004)**	(.004)
Abs. Diff. CHO	-.005	-.002	-.005	-.002
	(.008)	(.008)	(.008)	(.008)
Abs. Diff. Leverage	-.014	-.014	-.014	-.014
	(.009)	(.009)	(.009)	(.009)
Abs. Diff. Log(Sales)	-.005	-.004	-.005	-.004
	(.002)***	(.001)**	(.002)***	(.001)***
Abs. Diff. MTB	-.003	-.003	-.003	-.003
	(.002)	(.002)*	(.002)	(.002)*
Abs. Diff. Log(MKTCAP)	-.009	-.007	-.009	-.008
	(.002)***	(.002)***	(.002)***	(.002)***
Abs. Diff. ROE	-.008	-.007	-.007	-.007
	(.007)	(.007)	(.007)	(.007)
Abs. Diff. ROA	.024	.005	.025	.005
	(.032)	(.032)	(.032)	(.032)
Abs. Diff. EPS	-.002	-.003	-.002	-.003
	(.002)	(.002)	(.002)	(.002)
Abs. Diff. Stock Price	.0003	.0002	.0003	.0002
	(.0002)	(.0002)	(.0002)	(.0002)
Abs. Diff. AnnRet	-.011	-.013	-.011	-.013
	(.004)***	(.004)***	(.004)***	(.004)***
Abs. Diff. Volatility	-.181	-.157	-.189	-.165
	(.182)	(.180)	(.181)	(.180)
NDays	-.0002	-.0001	-.0001	-.00009
	(.0001)	(.0001)	(.0001)	(.0001)
Abs. Diff. PZDR	.035	.027	.034	.025
	(.030)	(.029)	(.030)	(.029)
Const.	.032	.025	.038	.042
	(.024)	(.025)	(.025)	(.025)*
Obs.	27833	27833	27833	27833
R^2	.399	.36	.399	.359

Panel C: Across Countries								
	Local Currency		US Currency		Local Currency		US Currency	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumA	.059	.071	.055	.079				
	(.033)*	(.033)**	(.033)*	(.033)**				
RhoA					.029	.034	.027	.039
					(.016)*	(.015)**	(.016)*	(.016)**
Pair ADR	.004	.006	.003	.006	.004	.005	.003	.006
	(.003)	(.003)**	(.003)	(.003)**	(.003)	(.003)**	(.003)	(.003)**
Pair MSCI	.006	.009	.006	.010	.006	.009	.006	.010
	(.003)**	(.002)***	(.003)**	(.002)***	(.002)**	(.002)***	(.003)**	(.002)***
Abs. Diff. CHO	-.0007	-.002	-.002	-.004	-.0007	-.002	-.002	-.004
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Abs. Diff. Leverage	.014	.009	.017	.011	.014	.009	.017	.011
	(.005)***	(.005)	(.005)***	(.005)**	(.005)***	(.005)	(.005)***	(.005)**
Abs. Diff. Log(Sales)	-.003	-.002	-.003	-.002	-.003	-.002	-.003	-.002
	(.0008)***	(.0008)**	(.0008)***	(.0008)**	(.0008)***	(.0008)**	(.0008)***	(.0008)**
Abs. Diff. MTB	-.001	-.0006	-.0006	-.00003	-.001	-.0006	-.0006	-.00003
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Abs. Diff. Log(MKTCAP)	-.002	.0003	-.001	.002	-.002	.0003	-.001	.002
	(.0009)*	(.0009)	(.0009)	(.0009)*	(.0009)*	(.0009)	(.0009)	(.0009)*
Abs. Diff. ROE	-.005	-.006	-.004	-.006	-.005	-.006	-.004	-.006
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Abs. Diff. ROA	.048	.036	.028	.025	.048	.036	.029	.025
	(.019)**	(.019)*	(.019)	(.019)	(.019)**	(.019)*	(.019)	(.019)
Abs. Diff. EPS	.0006	.0004	-.0001	.0008	.0006	.0004	-.0001	.0008
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Abs. Diff. Stock Price	-.0001	-.0001	-1.00e-05	-.0002	-.0001	-.0001	-1.00e-05	-.0002
	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)	(.0001)
Abs. Diff. AnnReturn	-.002	-.002	-.001	-.002	-.002	-.002	-.001	-.002
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Abs. Diff. Volatility	.126	.050	.116	-.004	.125	.050	.116	-.005
	(.125)	(.124)	(.125)	(.125)	(.125)	(.124)	(.125)	(.125)
NDays	-.00006	-.00004	-.0001	-.00007	-.00006	-.00004	-.0001	-.00007
	(.00005)	(.00005)	(.00005)**	(.00005)	(.00005)	(.00005)	(.00005)**	(.00005)
Abs. Diff. PZDR	.022	.015	.044	.021	.022	.015	.044	.021
	(.010)**	(.011)	(.010)***	(.011)**	(.010)**	(.011)	(.010)***	(.011)**
Const.	-.065	-.048	-.061	-.054	-.065	-.048	-.061	-.057
	(.015)***	(.016)***	(.015)***	(.015)***	(.015)***	(.016)***	(.015)***	(.015)***
Obs.	50221	50221	50221	50221	50221	50221	50221	50221
R^2	.226	.209	.23	.211	.226	.209	.23	.211

Table 2.4: ACN and MSCI Latin American Index

The table presents the results of the effect of ACN on excess comovement (pairwise correlation based on idiosyncratic returns) and the MSCI Latin American Index membership. On the top of each column appears the currency in which the returns are calculated and the model used to obtain the idiosyncratic returns. The variables $NumA$ and $RhoA$ measure the shared coverage between firm i and j (Muslu et al. (2014) and Israelsen (2014)). The control variables are winsorized at the 1st and 99th percentile. All regressions include industry-pair-year and country-pair-year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Across Countries	Local Currency		US Currency		Local Currency		US Currency	
Dependent Variable : Excess Comovement	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$NumA$	-.001	.022	-.018	.017				
	(.039)	(.039)	(.038)	(.038)				
$RhoA$					.003	.013	-.004	.012
					(.018)	(.018)	(.018)	(.018)
$NumA\ X\ MSCI$	.186	.150	.224	.191				
	(.062)***	(.062)**	(.062)***	(.063)***				
$RhoA\ X\ MSCI$					.180	.146	.217	.183
					(.062)***	(.061)**	(.062)***	(.063)***
$MSCI$	.005	.007	.004	.008	.005	.007	.004	.008
	(.003)*	(.003)***	(.003)	(.003)***	(.003)*	(.003)***	(.003)	(.003)***
ADR	.004	.006	.003	.007	.004	.006	.003	.007
	(.003)	(.003)**	(.003)	(.003)**	(.003)	(.003)**	(.003)	(.003)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Const.	-.065	-.048	-.057	-.057	-.065	-.048	-.060	-.057
	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***
Obs.	50221	50221	50221	50221	50221	50221	50221	50221
R^2	.226	.209	.23	.211	.226	.209	.23	.211

Table 2.5: Domestic vs International Analysts

The table presents the results of the effect of ACN on excess comovement (pairwise correlation based on idiosyncratic returns) and the differences between domestic and international analysts. On the top of each column appears the currency in which the returns are calculated and the model used to obtain the idiosyncratic returns. The variables $NumA$ and $RhoA$ measure the shared coverage between firm i and j (Muslu et al. (2014) and Israelsen (2014)). The control variables are winsorized at the 1st and 99th percentile. All regressions include industry-pair-year and country-pair-year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	Within Countries				Across Countries							
	Local Currency				Local Currency		US Currency		Local Currency		US Currency	
Dependent Variable : Excess Comovement	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$NumA - International$	.051	.051			.032	.037	.036	.036				
	(.014)***	(.014)***			(.015)**	(.015)**	(.015)**	(.016)**				
$NumA - Domestic$	.065	.060			.018	.018	.012	.022				
	(.010)***	(.010)***			(.012)	(.013)	(.012)	(.012)*				
$RhoA - International$			.103	.103					.058	.061	.067	.067
			(.024)***	(.025)***					(.026)**	(.026)**	(.027)**	(.027)**
$RhoA - Domestic$			.115	.105					.012	.017	.003	.022
			(.017)***	(.017)***					(.020)	(.020)	(.020)	(.020)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Const.	.047	.038	.022	.018	-.062	-.045	-.057	-.054	-.065	-.048	-.060	-.057
	(.025)*	(.025)	(.025)	(.025)	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***
Obs.	27833	27833	27833	27833	50221	50221	50221	50221	50221	50221	50221	50221
R^2	.4	.36	.399	.359	.226	.209	.23	.211	.226	.209	.23	.211

Table 2.6: MSCI Latin American Index Inclusion

The table presents the results of the effect of MSCI reviews on analyst coverage and comovement. We set up as $t = 0$ the quarter (year) in which a firm was added to the MSCI Latin American Index. Panel A displays the changes in analyst coverage and shared coverage before and after the MSCI reviews. We calculate the mean tests and report the p-values using one and two tails. Panel B reports the results about the effect of ACN on excess comovement (pairwise correlation based on idiosyncratic returns). The variables $NumA$ and $RhoA$ measure the shared coverage between firm i and j (Muslu et al. (2014) and Israelsen (2014)). Also, *Coverage* refers to number of analysts following a firm at the end of each quarter. The control variables are winsorized at the 1st and 99th percentile. All regressions include country-pair and year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Changes in Analyst Coverage and Network							
Quarter		*Coverage*			Ha:Diff>0	Ha:Diff≠0	
Before	After	Before	After	Difference	P-value	P-value	N
-4	4	6.06	7.43	1.371	0.0128	0.0255	194
-3	3	5.95	7.15	1.203	0.0222	0.0443	206
-2	2	6.20	6.77	0.565	0.1670	0.3339	216
-1	1	6.20	6.60	0.398	0.2423	0.4846	246
-1	4	6.35	7.44	1.086	0.0282	0.0564	232
-2	4	6.26	7.25	0.990	0.0466	0.0932	210
-3	4	5.97	7.34	1.372	0.0099	0.0198	204
Year		$NumA$			Ha:Diff>0	Ha:Diff≠0	
Before	After	Before	After	Difference	P-value	P-value	N
-2	2	0.145	0.170	0.025	0.0000	0.0001	1010
-2	1	0.143	0.164	0.153	0.0001	0.0002	1244
-1	1	0.136	0.151	0.0158	0.0004	0.0007	1866
-1	2	0.148	0.170	0.0225	0.0000	0.0001	1340
Year		*RhoA*			Ha:Diff>0	Ha:Diff≠0	
Before	After	Before	After	Difference	P-value	P-value	N
-2	2	0.309	0.357	0.047	0.0001	0.0002	1010
-2	1	0.304	0.343	0.039	0.0003	0.0007	1244
-1	1	0.290	0.320	0.297	0.0008	0.0015	1866
-1	2	0.313	0.356	0.043	0.0001	0.0002	1340

Panel B: Changes in Excess Comovement					
	(1)	(2)		(3)	(4)
Idiosyncratic Returns in Local Currency					
Model 1					
Δ *NumA (-1 vs.+1)*	.346 (.124)***	.366 (.132)***	Δ*RhoA(-1 vs.+1)*	.173 (.062)***	.185 (.064)***
Control Variables	No	Yes	Control Variables	No	Yes
Country-Pair FE	No	Yes	Country-Pair FE	No	Yes
Year FE	Yes	Yes	Year FE	Yes	Yes
Obs.	810	722	Obs.	810	722
R^2	.039	.099	R^2	.058	.1
Model 2					
Δ *NumA (-1 vs.+1)*	.267 (.119)**	.302 (.131)**	Δ*RhoA(-1 vs.+1)*	.144 (.059)**	.157 (.064)**
Control Variables	No	Yes	Control Variables	No	Yes
Country-Pair FE	No	Yes	Country-Pair FE	No	Yes
Year FE	Yes	Yes	Year FE	Yes	Yes
Obs.	810	722	Obs.	810	722
R^2	.029	.081	R^2	.03	.082
Idiosyncratic Returns in US Dollars					
Model 1					
Δ *NumA (-1 vs.+1)*	.288 (.124)**	.294 (.129)**	Δ*RhoA(-1 vs.+1)*	.151 (.062)**	.152 (.063)**
Control Variables	No	Yes	Control Variables	No	Yes
Country-Pair FE	No	Yes	Country-Pair FE	No	Yes
Year FE	Yes	Yes	Year FE	Yes	Yes
Obs.	810	722	Obs.	810	722
R^2	.032	.1	R^2	.033	.1
Model 2					
Δ *NumA (-1 vs.+1)*	.236 (.119)**	.284 (.129)**	Δ*RhoA(-1 vs.+1)*	.129 (.059)**	.150 (.064)**
Control Variables	No	Yes	Control Variables	No	Yes
Country-Pair FE	No	Yes	Country-Pair FE	No	Yes
Year FE	Yes	Yes	Year FE	Yes	Yes
Obs.	810	722	Obs.	810	722
R^2	.033	.09	R^2	.034	.09

Table 2.7: Brokerage Coverage Network (BCN) and Comovement

The table presents the results of the effect of ACN on return comovement (raw pairwise correlation). On the top of each column appears in which currency the returns are calculated. The variables $NumB$ and $RhoB$ measure the shared coverage at brokerage house level between firm i and j (Muslu et al. (2014) and Israelsen (2014)). The control variables are winsorized at the 1st and 99th percentile. All regressions include industry-pair-year and country-pair-year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	Full Sample				Within-Country		Across-Country	
	Local Currency	US Currency	Local Currency	US Currency	Local Currency		US Currency	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NumB	.077	.079			.089		.045	
	(.008)***	(.007)***			(.013)***		(.010)***	
RhoB			.033	.034		.043		.018
			(.004)***	(.003)***		(.006)***		(.005)***
Pair ADR	.015	.012	.015	.012	.017	.017	.013	.013
	(.002)***	(.002)***	(.002)***	(.002)***	(.005)***	(.005)***	(.002)***	(.002)***
Pair MSCI	.025	.023	.025	.023	.030	.030	.022	.023
	(.002)***	(.002)***	(.002)***	(.002)***	(.004)***	(.004)***	(.002)***	(.002)***
Abs. Diff. CHO	-.007	-.009	-.007	-.009	-.009	-.009	-.009	-.009
	(.003)**	(.003)***	(.003)**	(.003)***	(.007)	(.007)	(.004)**	(.004)**
Abs. Diff. Leverage	.004	-.004	.004	-.004	-.006	-.006	.009	.009
	(.004)	(.003)	(.004)	(.003)	(.008)	(.008)	(.004)**	(.004)**
Abs. Diff. Log(Sales)	-.0004	-.001	-.0004	-.001	-.002	-.002	.0002	.0002
	(.0007)	(.0006)**	(.0007)	(.0006)**	(.001)	(.001)	(.0007)	(.0007)
Abs. Diff. MTB	-.003	-.001	-.003	-.001	-.002	-.002	-.002	-.002
	(.0008)***	(.0007)**	(.0008)***	(.0007)*	(.001)	(.001)	(.0009)**	(.0009)**
Abs. Diff. Log(MKCAP)	-.00009	.0008	-.0002	.0007	-.002	-.002	.002	.002
	(.0007)	(.0006)	(.0007)	(.0006)	(.001)	(.001)*	(.0008)**	(.0008)**
Abs. Diff. ROE	.008	-.004	.008	-.004	.006	.007	.008	.008
	(.003)***	(.003)	(.003)***	(.003)	(.006)	(.006)	(.004)**	(.004)**
Abs. Diff. ROA	-.145	-.153	-.145	-.153	-.215	-.215	-.181	-.181
	(.014)***	(.013)***	(.014)***	(.013)***	(.028)***	(.028)***	(.017)***	(.017)***
Abs. Diff. EPS	-.0002	-.0008	-.0002	-.0008	.0001	.00009	-.003	-.003
	(.001)	(.0009)	(.001)	(.0009)	(.002)	(.002)	(.001)**	(.001)**
Abs. Diff. Stock Price	.0002	.0007	.0002	.0007	.0006	.0006	.0007	.0007
	(.0001)**	(.00008)***	(.0001)**	(.00008)***	(.0002)***	(.0002)***	(.0001)***	(.0001)***
Abs. Diff. AnnRet	-.032	-.039	-.032	-.038	-.043	-.043	-.035	-.035
	(.002)***	(.001)***	(.002)***	(.001)***	(.003)***	(.003)***	(.002)***	(.002)***
Abs. Diff. Volatility	-.105	-.761	-.107	-.763	.225	.222	-.737	-.738
	(.089)	(.082)***	(.089)	(.082)***	(.163)	(.163)	(.106)***	(.106)***
Number of Days	-.0003	-.0003	-.0003	-.0003	-.0004	-.0004	-.0003	-.0003
	(.00004)***	(.00004)***	(.00004)***	(.00004)***	(.0001)***	(.0001)***	(.00004)***	(.00004)***
Abs. Diff. PZDR	-.131	-.111	-.132	-.112	-.241	-.243	-.095	-.095
	(.009)***	(.008)***	(.009)***	(.008)***	(.026)***	(.026)***	(.009)***	(.009)***
Const.	.223	.320	.223	.321	.446	.425	.233	.229
	(.022)***	(.022)***	(.022)***	(.022)***	(.017)***	(.018)***	(.014)***	(.014)***
Obs.	78054	78054	78054	78054	27833	27833	50221	50221
R^2	.513	.675	.513	.674	.598	.598	.665	.665

Table 2.8: Brokerage Coverage Network (BCN) and Excess Comovement

The table presents the results of the effect of BCN on excess comovement (pairwise correlation based on idiosyncratic returns). On the top of each column appears the currency in which the returns are calculated and the model used to obtain the idiosyncratic returns. The variables $NumB$ and $RhoB$ measure the shared coverage at brokerage house level between firm i and j (Muslu et al. (2014) and Israelsen (2014)). The control variables are winsorized at the 1st and 99th percentile. All regressions include industry-pair-year and country-pair-year fixed effects and standard errors are clustered at the firm-pair level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

	Full Sample				Within Countries				Across Countries							
	US Currency				Local Currency		Local Currency		Local Currency		US Currency		Local Currency		US Currency	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
$NumB$	.022	.028			.025	.044			.003	.007	.008	.013				
	(.009)**	(.009)***			(.015)*	(.015)***			(.012)	(.012)	(.012)	(.012)				
$RhoB$			.008	.011			.012	.021					-.002	-.0005	-.00003	.003
			(.004)*	(.004)**			(.007)*	(.007)***					(.006)	(.006)	(.006)	(.006)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Const.	.039	.041	.039	.041	.045	.033	.038	.025	-.062	-.045	-.057	-.054	-.071	-.054	-.068	-.064
	(.021)*	(.019)**	(.021)*	(.019)**	(.024)*	(.024)	(.025)	(.025)	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***	(.015)***
Obs.	78054	78054	78054	78054	27833	27833	27833	27833	50221	50221	50221	50221	50221	50221	50221	50221
R^2	.219	.185	.219	.185	.395	.356	.395	.356	.226	.209	.23	.211	.226	.209	.23	.211

Table 2.9: Stock Price Synchronicity

The table presents the results of the effect of ACN on stock return synchronicity. *International Degree* measures the number of across-country connections of a firm in each year. Also, *Coverage* refers to number of analysts following a firm at the end of each calendar year The control variables are winsorized at the 1st and 99th percentile. All regressions include industry and country-year fixed effects and standard errors are clustered at the firm level. See Appendix B for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Dependent Variable :	*Model 1:* $\Delta SyncR^2$				*Model 2:* $\Delta SyncR^2$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
International Degree			.002	.001			.002	.001
			(.0004)***	(.0005)**			(.0004)***	(.0005)**
Coverage	.001	.001	.0004	.0008	.001	.002	.0002	.001
	(.0005)***	(.0006)***	(.0005)	(.0006)	(.0005)***	(.0005)***	(.0005)	(.0006)
ADR	-.004	-.002	-.003	-.001	-.005	-.001	-.004	-.00009
	(.005)	(.006)	(.005)	(.006)	(.004)	(.005)	(.004)	(.005)
MSCI	.009	.006	.008	.005	.007	.003	.007	.005
	(.005)*	(.006)	(.005)	(.006)	(.005)	(.006)	(.005)	(.006)
CHO		.026		.023		.021		.021
		(.011)**		(.011)**		(.009)**		(.009)**
Log(Sales)	-.001	-.0008	-.002	-.001	-.001	-.0001	-.003	-.003
	(.002)	(.003)	(.002)	(.003)	(.002)	(.002)	(.002)	(.003)
MTB	.005	.005	.004	.004	.004	.004	.001	.001
	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.003)	(.004)
Leverage	.007	.020	.008	.023	.004	.006	.005	.009
	(.011)	(.017)	(.011)	(.017)	(.012)	(.016)	(.011)	(.016)
Tangibility	.004	-.001	.006	-.0003	.007	.002	.013	.0006
	(.010)	(.011)	(.010)	(.011)	(.010)	(.012)	(.010)	(.012)
ROA	-.012	.045	-.012	.044	-.060	-.030	-.087	-.056
	(.060)	(.047)	(.059)	(.047)	(.057)	(.056)	(.065)	(.066)
ROE	.002	-.0004	.004	.001	.016	.014	.019	.016
	(.015)	(.010)	(.014)	(.010)	(.014)	(.012)	(.014)	(.013)
Volatility	.620	.529	.611	.509	.349	.235	.182	.222
	(.319)*	(.466)	(.316)*	(.466)	(.327)	(.410)	(.314)	(.438)
NDays	.00003	-.00009	.00002	-.00007	-9.98e-06	-.00006	-.00008	-.00003
	(.0001)	(.0002)	(.0001)	(.0002)	(.0001)	(.0002)	(.0001)	(.0003)
PZR	.052	.035	.052	.040	.033	.028	.017	.041
	(.029)*	(.050)	(.029)*	(.050)	(.031)	(.056)	(.031)	(.058)
Const.	.008	-.014	.015	-.014	.042	-.015	.067	.016
	(.067)	(.101)	(.066)	(.100)	(.067)	(.098)	(.069)	(.105)
Obs.	2169	1398	2169	1398	2169	1398	2088	1348
R^2	.098	.14	.105	.143	.099	.139	.113	.147

Chapter 3

Performance Pay, Catering Incentives and Functional Background

3.1 Introduction

It is common knowledge that for firms to survive they must adapt dynamically to market competition or technological changes. For that reason, firms choice different business strategies over the time to be successful in the long run. They do so, by focusing their effort on improving firm profitability or firm growth depending on the firm's performance in the short-term (Boumgarden et al. (2012) and Nickerson and Zenger (2002)). Previous studies argue that in order to improve firm profitability or growth it is necessary change the leadership of the firm. Specifically, bring a CEO who has a functional background (or previous experience) associated with growth- or profit-oriented activities (Yen (2014) and Elsaid et al. (2015)).[1] However, the main drawback of the previous studies is the lack of consideration of executive incentive plans as a potential tool to improve firm performance with respect to one of these activities (or both).

The last financial crisis raised several questions regarding the compensation plans of executives. Not only for the large size of their compensation, but also for the way that

[1] We also refer to growth-oriented activities as exploration activities and profit-oriented activities as exploitation activities.

those packages induced managers to engage in risky activities. However, before December 2006 firms were not required to disclose details of compensation packages (stocks, bonuses or grants) tied to performance goals. Then, as a consequence of the subprime crisis, the Securities and Exchange Commission (SEC) issued new rules to enforce the disclosure of detailed information about the compensation contracts allowing researchers to collect new and detailed information about managers' incentive plans. Specifically, the fraction of the total compensation tied to financial and non-financial goals.

De Angelis and Grinstein (2011, 2015) hand-collect the terms of the CEO compensation contracts from each firm's proxy statement after 2006, to study their characteristics and the cross-sectional characteristics of the firms which employ them. Also, they look at the use of relative performance evaluation in CEO compensation contracts. Moreover, Bennett et al. (2015), provide evidence on the eight most common accounting metrics that firms employ to tie compensation to performance goals for the 750 largest firms in the US. The most frequent accounting metrics are sales and earnings growth, operating income, cash flows, EBIT, EBITDA, ROE and EPS. Also, they show that linking executive compensation to accounting goals has several costs in terms of manipulation of reported accounting metrics to achieve compensation goals. Furthermore, Alok and Gopalan (2014) employ the new detailed information about performance pay to explain the divisional manager compensation design in multi-division firms. Our paper is closely related to this new stream of literature that tries to understand the benefits and costs of designing executive compensation using accounting performance goals.

Hence, the scope of this study is to understand how board of directors tie the compensation of managers to several accounting metrics (pay for performance) and provide empirical evidence regarding the combined effect of those incentives plans and the functional background of CEOs on firm performance. Moreover, in the first part of the paper we address the research question: *How do firms decide which metrics to focus on when they are designing compensation plans in order to encourage managers to pursue profit- and/or growth-oriented activities?* We propose that board of directors consider short-term mispricing associated with the investor demand (Catering Incentives) to design the executive compensation according the stock market's preferences for specific accounting metrics. Following the catering theory (Baker and Wurgler (2004a,b) and Polk and Sapienza (2009)), we measure the market's preference as the difference between the average market-to-book ratio of firms in the top of the distribution and firms in the bottom according to their accounting performance on those metrics. We call this measure *Value Premium*. We argue that boards of directors cater to investor preferences (higher Value Premium) for firms with better performance on certain accounting metrics.

The decision of which metrics to focus on might has consequences in the short- and long-term performance. Designing a compensation plan based on investor demand for specific accounting metrics might affect firm focus regarding exploration and exploitation activities (growth- or profit oriented activities). If we classify sales growth as an output oriented accounting metric and earnings growth, operating income, cash flows, EBIT, EBITDA, ROE and EPS as accounting metrics associated with profit activities, we can argue that firms can induce to focus to improve not only through CEO leadership succession, but also through the CEO compensation plan.

Then, in the second part of the paper we address two questions related to the consequences of compensation designs on firm performance conditional to the functional background of CEOs: *Do awards based on performance goals affect firm performance after controlling for the CEO functional background?* CEO succession posits that functional background is a key component of the firm's long-term success. However, we extend this idea by arguing that pay for performance is also a key component in firm performance. Because we are able to observe detailed data regarding performance pay, we provide evidence that both CEO functional background and performance pay positively affect firm performance. We show that they complement each other and, more interestingly, the compensation plans are more important for recently appointed CEOs (less than two years).

The third question is related to the consequences of having performance pay aligned with the CEO's functional background: *Do firms with aligned CEO incentives have better performance?* In the process of designing executive compensation with performance metrics according to the *Value Premium*, firms can tie CEO compensation to performance metrics associated only with exploration, only with exploitation, or from both activities. However, the functional background of the CEO may not be consistent with those incentives. For example, a CEO has a functional background in sales and marketing, but she has an incentive plan tied to profitability metrics such as EPS and EBITDA. Even though the incentives seem to be focused on exploitation activities, they are not aligned with her functional background. A priori we expect that the first implication of compensation design is that firms with aligned incentives have better performance in the short- and long-run.

We construct the sample from standard sources covering the sample period 2006-2012. From CRSP-COMPUSTAT we obtain the accounting information of firms and stock prices at the end of the fiscal year. The performance metrics on which firms base manager compensation is obtained from Incentive Lab (IL).[2] From ExeComp we collect the CEO and executive compensation. Specifically, our main performance pay variable is the percentage of the total compensation linked to specific accounting metrics. Finally, corporate governance data comes from Riskmetrics.

We divide the results in two parts. The first part is related to compensation design; the second part is related to the implications of compensation design on firm performance. Our results suggest a direct relationship between market preferences *(Value Premium)* for performance accounting metrics and executive compensation. Boards of directors tie the compensation of CEOs and top executives according to investor demand in the previous year. In terms of economic magnitude, one standard deviation increase in the *Value Premium* increases on average 0.11%-0.18% (0.11%-0.15%) the performance pay of CEOs (top executives). Considering that in our sample on average the performance pay of the eight accounting metrics is 1%, the effect of the investors demand is economically significant. Also, our results are robust even after controlling for firm-year fixed effects. In addition, powerful CEOs are less willing to have compensation tied to accounting metrics when the market's preferences suggest that firms increase the performance pay.

The second part of the results is related to the effect of CEO compensation design

[2] We work with the same data set employed by Alok and Gopalan (2014) and Bennett, Bettis, Gopalan, and Milbourn (2015).

on firm performance. Functional background and performance pay are complementary determinants of firm performance. However, the compensation plans affect mainly the short- and medium-term firm performance while the functional background has a higher impact over the long-run. In our results, when firms have a CEO with the functional background consistent with either exploration or exploitation activities, they have on average 3.1%, 5.0% and 8% higher performance in the short-, medium- and long-run, respectively.

We also provide evidence that CEO tenure plays an important role on the effectiveness of performance pay on firm performance. We find that the performance pay is important only for recently appointed CEOs and it has a long lasting effect. In terms of economic magnitudes, a one standard increase in the Performance Pay improves firm performance by 1.5%, 2.7% and 3.3% in the short-, medium- and long-run, respectively. When we consider older CEOs, we do not find any effect of the compensation linked to accounting metrics on firm performance. Furthermore, we provide evidence that firms with aligned incentives have better performance in the short-, medium- and long-run. However, we only find a strong and positive relation in the subsample of CEOs with less than two years of tenure. Overall, firms that provide aligned incentives for their recently appointed CEOs outperform firms with misaligned incentives by 6.4%, 11.3% and 11.2% in the short-, medium- and long-run, respectively. Our result contributes to the literature of executive compensation and CEO succession by showing that together, functional background and incentives plans, are crucial to have successful firms in the long-run.

The rest of the paper is organized as follows. Section 3.2 develops our hypothesis. Section 3.3 describes our empirical design and key variables. Section 3.4 discusses the data and summary statistics. Section 3.5 presents the results of our empirical tests, while conclusions are discussed in Section 3.6. Definitions of all variables are in Appendix C.

3.2 Hypotheses Development

Our paper is related to two streams of literature. The first one is the catering theory. A growing literature has shown that investors do not always trade based on the fundamental values of firms and their demand for securities can deviate from fundamentals in the short-term. Hence, managers rationally exploit these deviations and cater to investor demand in order to maximize the firm's value in the short-term. These actions can be changes in corporate policies in order to attract investors who are demanding firms with certain corporate policies (Catering Theory: Baker and Wurgler (2004)). On the other hand, managers, in the short-term, can strategically choose the best time for using debt or equity in order to exploit deviations in the market value of the firm from its fundamentals (Market Timing: Baker and Wurgler (2002)). For instance, firms can issue equity when the stock price is overvalued or repurchase shares when the stock is undervalued.

Baker and Wurgler (2004a) provide evidence that firms decide to start (stop) the payment of dividends when the investor demand for dividend paying firms is high (low). Managers cater to investors by paying dividends when investors put a stock price premium on payers, and by not paying when investors prefer non-payers. Li and Lie (2006) extend the previous work considering changes in dividend pay. They show that the decision to change the dividend and the magnitude of the change depend on stock market preferences for higher dividend payers versus lower dividend payers. In the catering theory, the stock market preferences are measured as the premium that investors pay for firms with certain corporate policies which at that moment are attractive for investors. The typical measure for the value premium is the difference in the market-to-book ratio of firms on the top of the distribution with respect to a corporate policy of interest (dividend payout policy or investment) versus firms that are on the bottom.

Polk and Sapienza (2009) test the catering theory on investment decisions. Using another proxy for mispricing, abnormal accruals, they show that firms with higher abnormal accruals tend to invest more as compared to firms with lower abnormal accruals. This proxy for mispricing is used because periods of higher abnormal accruals are followed by periods of lower returns. Hence, managers tend to boost short-run share prices by catering to current sentiment. One paper related to our study, which show that compensation plans and investor preferences are connected is the empirical evidence provided by Geiler and Renneboog (2016). They show that in the UK market CEO compensations plans directly linked to payout policies and their effect is even stronger than investor preferences. In this paper, we want to provide evidence that boards of directors cater to investor demands for firms with better performance based on certain accounting metrics when they design executive performance pay.

The second stream of literature is related to organizational vacillation. This literature suggests that firms tend to change organizational design in order to achieve better long-run performance and survive in a competitive industry. Nickerson and Zenger (2002) show that firms switch their structure from centralization to decentralization in order to support exploitation or exploration activities, respectively (Sequential Organizational Vacillation). Yen (2014) provides empirical evidence about the vacillation theory. The author shows that firms change their strategic business focus over time between output (growth) and throughput (firm's profitability) in order to achieve a successful performance in the long-run. However, the sequential organizational vacillation is driven by the background of CEOs. Hence, in order to induce a change in the business activity of firms, they have to replace the CEO and bring in a new leader with the functional background consistent with the business activity that firms want to implement. Elsaid et al. (2015) utilize a sample of 832 successions to examine how boards of directors select and determine the functional backgrounds of the incumbent CEOs. They find that outgoing CEO and firm characteristics influence the choice of successor's functional background. Also, in the same line that Yen (2014), the authors find that firms are more likely to change the functional background of the new CEO relative to the incumbent CEO when firms have poor performance.

Aghion and Stein (2008) provide an important theoretical model related to our work. They develop a model in which a firm endogenously changes the business strategy from sales growth to profit margin or vice versa depending on the current investor demand for those strategies. When managers care about the current stock price, they tend to focus their efforts on increasing sales growth when there is a premium for growing firms. On the other hand, in times when investors prefer firms which have higher levels of profitability, managers tend to focus on reducing costs and improving efficiency. In addition, the model develops a dynamic behavior in which a firm can switch the business strategy many times in different periods. In this paper we propose that boards of directors cater to investor demand for firms with better performance in certain accounting metrics. Boards of directors tie the managers' awards to those metrics in order to boost the stock price in the short-term. Thus, the first hypothesis is:

Hypothesis 1: *Firms decide the executive performance pay based on the Value Premium associated with exploration and exploitation activities.*

When the market prefers firms with metrics associated with exploration activities as compared to exploitation activities, the board of directors will cater to investor demand and will focus the CEO compensation on accounting metrics associated with exploration activities. Conversely, if the market prefers more exploitation, the board of directors will focus CEO compensation on metrics linked to the exploitation activity.

The last hypothesis is related to the performance pay and functional background. We test whether functional background and CEO compensation work as substitutes or complementary factors that affect firm performance in the short- and long-term. Additionally, we test whether firms that have compensation pay aligned with the CEO functional background outperform firms with misaligned incentives.

Hypothesis 2a: *Performance pay and CEO functional background together are important determinants of firm performance.*

Hypothesis 2b: *Firms with aligned incentives outperform firms with misaligned incentives.*

3.3 Empirical Design and Key Variables

We are interested in understanding how firms design executive compensation. Our first hypothesis posits that firms consider investor preferences for exploration or exploitation activities to design performance pay. Specifically, the board of directors rationally caters to investor demand by tying the performance of executives to the accounting metrics associated with growth- and profit-oriented activities. We create a variable called *Value Premium* which measures the premium that investors pay for firms with better performance on the accounting metrics of interest as compared to firms with worse performance. Notably, firms can either tie the executive compensation to accounting metrics in level or in growth terms (Bennett, Bettis, Gopalan, and Milbourn (2015)). However, using an accounting goal in level terms implies a growth performance goal with respect to the previous year. Hence, in this paper we calculate the *Value Premium* using the firm performance of the eight accounting metrics in growth terms such as sales growth or EPS growth rather than the sales or EPS level.

The variable $Value\ Premium_{jkt}$ is a vector that contains the natural logarithmic difference of the average market-to-book ratios between firms with higher accounting performance (in the top of the distribution) versus firms with lower accounting performance (in the bottom of the distribution). For each year and two-digit SIC code industry classification we rank the firms based on their performance with respect to the eight accounting metrics identified above. We use the percentiles p85 (p15), p80 (p20) and p75 (p25) as cutoffs to define the top (bottom) of the distribution and calculate the log difference in the average market-to-book ratios.

For instance, if we want to determine the value premium for *sales growth* we sort the firms from highest growth rate in sales to firms with lowest growth rate in each year and by the two-digit SIC code industry classification. Then, we calculate the average of market-to-book ratio of the firms which are in the top (high growth) and bottom (low growth) of the *sales growth* distribution and we perform the log difference in the average market-to-book ratio between those two groups.[3] Hence, if we use as cutoffs the percentiles p80 (top quintile) and p20 (bottom quintile), we calculate the average market-to-book ratio for the group of firm that are in the highest quintile (above p80) and the group of firms in the lowest quintile (equal or below p20). We define the Market-to-Book ratio (MTB) as the market value of assets (market value of common shares plus preferred stock liquidating value plus short and long debt minus deferred taxes and investment tax credit) divided by the total book asset value.[4]

$$Value\ Premium_{jkt} = Ln(\overline{MTB_{HG}})_{jkt} - Ln(\overline{MTB_{LG}})_{jkt}$$

Where $\overline{MTB_{HG}}$ and $\overline{MTB_{LG}}$ are the average market-to-book ratio for the firms with high growth and low growth in the industry j on the accounting metric k for the year t, respectively. When the difference is positive investors prefer firms with higher growth rates for a given performance metric. In other words, investor demand gives a premium to firms with better performance on those metrics which interest investors. Hence, if a firm wants to boost the current stock price, the board of directors should design CEO compensation that is highly sensitive to the performance metrics consistent with investor demand. A priori, we expect a positive coefficient associated with the $Value\ Premium_{jkt}$ variable. Additionally, in order to reduce endogeneity concerns we use the first lag of the $Value\ Premium_{jkt}$ variable. To test the first hypothesis, we estimate the following model:

$$Performance\ Pay_{ikt} = \alpha + \beta_1 Value\ Premium_{jkt-1} + \beta_2 Peer\ Pay_{jkt-1} + \beta_3 Ind.\ Performance_{jkt} + \gamma Z_{it} + \lambda_i + \mu_t + \epsilon_{ikt} \tag{3.1}$$

Where subscript i refers to the firm, subscript j refers to the two-digit SIC code industry classification, and subscript t refers to time in years. In addition, subscript k refers to the eight performance metrics linked to the executive compensation. The dependent variable

[3] We require at least ten industry-year observations to calculate the *Value Premium* for a given metric

[4] Compustat items: *(prcc_f*csho+pstkl+dlc+dltt-txditc)/at*

$Performance\ Pay_{ikt}$ is a vector that contains the fraction of the total executive compensation (which is the sum of annual salary, bonus, present value of stock awards, present value of stock option awards, other annual compensation, long-term incentive payouts, and other cash payouts) tied to the accounting metric goal k. According to Bennett, Bettis, Gopalan, and Milbourn (2015). Firms mostly use (number of grants) EPS, Sales, Operating Income, Earnings, EBITDA, EBT, EBIT and Cash flow from operations to tied compensation to goals. However, in this paper we use ROE rather than EBT because the latter has tied, on average, a lower fraction of the total compensation than the former. Hence, our main accounting metrics are EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT.[5] Firms can tie awards to accounting metrics using either target goals in level or growth terms and also for short and long time horizons. In this paper we sum the portion of the compensation associated with level and/or growth for each accounting metric. Thus, the $Performance\ Pay_{ikt}$ variable is the sum of the short- and long-term incentives associated with the accounting goals defined in level and growth terms.

Moreover, the first accounting performance metric, sales growth, is associated with exploration activities. The remaining seven measures are related to exploitation activities. These performance measures, performance pay measures and control variables are winsorized at 1% level to mitigate the effect of outliers. Also, we cluster the standard errors at firm-year level.

In addition, the matrix Z_{it} contains several controlling variables such as: stock return in the current year, sales growth, the ratio cash-flows-to-total-assets, bid ask spread, and firm size. Moreover, we include the variable $Industry\ Performance_{jkt}$, which is the average performance of the firm's peers in the same industry (two-digit SIC code), with respect to the eight metrics mentioned above in growth terms. And the variable $Peer\ Pay_{jkt-1}$, which is a vector that contains executive compensation tied to the eight performance metrics of peer firms in the same industry classification in the previous year. We expect that firms tend to follow the CEO compensation of their peers in the same industry. We include corporate governance measures such as Power Index (Morse et al. (2011)), which is a variable with a

[5] See Appendix C for a complete definition of the accounting metrics

range from 1 to 3 depending on the number of titles that a CEO holds in the firm. If the CEO is the president of the firm and also the chairman of the board the index is equal to 3. If the CEO is only the chairman of the board the index is equal to 2. Finally, if the CEO is not the chairman of the firm the index is equal to 1. Moreover, we include a dummy variable that takes the value of 1 if the firm has an Entrenchment Index in the bottom 40% of the distribution. Also, we include a independent directors dummy variable, which take the value of 1 if a firm has a percentage of independent directors in the top 40% of the distribution. Lastly, we control for firm- and year-fixed effects.

To test the second hypothesis, we need the functional background of the CEO. Leadership vacillation argues that the CEO has to have a functional background consistent with the business strategy (growth vs. profit oriented) that firms want to implement. Unfortunately, classifying the functional background of managers is very difficult because the classification itself is open to different interpretations. However, we follow the the same methodology provided by Yen (2014). The author classifies the functional background into ten categories: (1) consulting and strategic planning, (2) founder entrepreneur, (3) sales, marketing, and merchandising, (4) product R&D and technology, (5) general management, (6) process engineering, (7) finance and accounting, (8) production, manufacturing, and operation, (9) law and general counsel, and (10) other functions, such as human resources and industrial relations. Then, the first five categories (from 1 to 5) are classified as exploration or growth oriented and the latter five categories (from 6 to 10) are classified as exploitation or profit oriented.[6]

Since it is difficult to determine the functional background for all the CEOs in our sample period, we focus our effort only for firms in the S&P-500. We carefully read the curriculum vitae of each CEO from official sources. The most important sources to identify the functional background are the biographies provided by Capital IQ and Equilar Atlas. We track the previous job of managers before being appointed as CEO of the firm. We follow closely the methodology used in Yen (2014). We read each biography and we classify

[6] Elsaid et al. (2015) classify the functional background in three groups: (1) Output: sales, marketing, and merchandising. (2) Throughput: product R&D and technology, process engineering, production, manufacturing, and operation. (3) Peripheral: finance and accounting, production, manufacturing, and operation, law and general counsel.

a CEO with experience in one of the ten previous categories if she worked at least five years in a job related to one of those categories. We are focus on work experience rather than educational background because most CEOs have MBAs or certificates in business, but they have bachelors degrees in a wide spectrum of fields. Hence, only considering the educational background would lead us to a noisy variable. It is important to highlight that a CEO can have functional backgrounds that are both growth and profit oriented.

We obtain the functional background of 480 CEOs, excluding financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4949) firms). In our sample, 173 CEOs are solely profit oriented, 256 are solely growth oriented and 51 CEOs have both functional backgrounds. Our regression to test the second hypothesis is the following:

$$Firm\ Performance_{ikt}^{t,t+\Delta t} = \alpha + \beta_1 Functional\ Background_{ikt} + \beta_2 Performance\ Pay_{ikt} + \beta_3 Ind.\ Performance_{jkt}^{t,t+\Delta t} + \delta_{it} + \epsilon_{it} \tag{3.2}$$

We use three time horizons to calculate the firm performance for each accounting metrics k. $Firm\ Performance_{ikt}^{t,t}$ is the accounting metric growth k in the current fiscal year ($\Delta t = 0$). $Firm\ Performance_{ikt}^{t,t+1}$ is the average growth between the current year and the next year ($\Delta t = 1$). And $Firm\ Performance_{ikt}^{t,t+2}$ is the average growth between the current year, the next year and the year after ($\Delta t = 2$). The dummy variable $Functional\ Background_{ikt}$ is the functional background of the CEO in the firm i. For instance, if the CEO has a functional background that is sales oriented (growth oriented), the variable $Functional\ Background_{ikt}$ will be equal to one in the accounting metric sales growth and zero otherwise. In addition, if both performance pay and functional background are important determinants of firm performance, we should expect a positive sign on the coefficient associated with β_1 and β_2. Lastly, we control for industry performance ($Ind.\ Performance_{jkt}^{t,t+\Delta t}$) for the same time horizon in which firm performance is calculated and we employ firm-year fixed effects (δ_{it}).

The next part of the second hypothesis is to test whether firms that align incentives (performance pay) of the CEO with her functional background outperform firms with misaligned incentives. In other words, we test whether firms with compensation incentives associated with either exploration or exploitation activities have better performance when those incentives are consistent with the functional background of the CEO. Specifically, we say that a firm has growth (profit) incentives if the firm ties the CEO compensation to sales (profitability measures) performance goals. In other words, a firm has growth (profit) incentives when the $Performance\ Pay_{ikt}$ variable is greater than zero for the sales (profitability) accounting metric. It is important to highlight that firms can simultaneously provide growth and profit incentives. In fact, in our sample of 2,106 firm-year observations (only SP&500 firms), we have 460 firm-year observations with both incentives and 78 (634) firm-year observations with only growth (profit) incentives.

Then, we create a dummy variable that combines the functional background with the focus sales (profit) incentives. Our variable of interest is $Aligned\ Incentives_{ikt}$, that takes the value of one if a firm provides focus incentives consistent with the functional background of the CEO. Given that firms can provide simultaneously growth and profit focus incentives and CEOs can have the two types of functional background, we have five cases in which firms have aligned incentives with respect to exploration and/or exploitation activities. First, firms only provide growth focus incentives and the CEO is output oriented (exploration aligned incentives). Second, firms only provide profit focus incentives and the CEO is profit oriented (exploitation aligned incentives). Third, firms provide growth and profit focus incentives and the CEO is output oriented (exploration aligned incentives). Fourth, firms provide growth and profit focus incentives and the CEO is profit oriented (exploitation aligned incentives). Finally, firms provide growth and profit focus incentives and the CEO has both functional backgrounds (exploitation and exploration aligned incentives). We run the following regression to test the effect of aligned incentives on firm performance.[7]

$$Firm\ Performance_{ikt}^{t,t+\Delta t} = \alpha + \beta_1 Aligned\ Incentives_{ikt} + \beta_2 Ind.\ Performance_{jkt}^{t,t+\Delta t} + \gamma Z_{it} + \lambda_i + \mu_t + \epsilon_{it} \quad (3.3)$$

[7] As robustness test we employ firm-year fixed effects (δ_{it})

We expect that β_1 is positive. Firms with aligned incentives should have better performance in the short- and long-term.

3.4 Data and Summary Statistics

The final sample for our paper comes from standard sources and covers the time period 2006 to 2009. From CRSP-COMPUSTAT, we obtain the financial variables of firms and stock prices. From ExeComp we collect the top executives' information for the 750 largest US firms. Moreover, the accounting performance goals on which firms based managers' compensation come from Incentive Lab (IL). Our data set starts in 2006 because data available regarding the accounting goals was not disclosed until that year (SEC standardized disclosure requirements for plan-based awards). Our final sample contains 4,460 CEO-year observations and 4,414 top excutives-year observations for the average performance pay compensation.

In Table 3.1, we provide the summary statistics for the main variables of our paper. Specifically, in Panel A we provide information about the fraction of the total compensation tied to eight accounting metrics. For instance, on average the performance pay tied to sales growth is 2% for either CEOs and Top Executives. In addition, the performance pay linked to earnings per share (EPS) is the most important variable in our sample; the fraction linked to EPS is on average 4% of CEO total compensation. It is important to highlight that the compensation linked to growth-oriented activities is lower as compared to profit-oriented activities. The average of the seven metrics linked to profit activities (Total Profit accounting metrics) is 10% and 8% for the CEO and Top Executives samples, respectively.

In panel B we show our proxy for investor demand (*Value Premium*) with respect to the eight performance metrics. Consistent with our hypothesis, the *Value Premium* is on average positive for all the accounting metrics and using the three cutoffs (percentile p85(p15), p75(p25), p80(p20)). Sales growth is the accounting metric with higher *Value Premium,* which is on average 0.5 when we use the percentiles p85(p15) and 0.46 when we use quartiles. Regarding the most important accounting metrics in our sample, EPS, we find that the *Value Premium* is on average 0.21 for all the cutoffs.

Panels C and D show the summary statistics at firm level. On average, firms tie 1% of the CEO and Top Executives total compensation to the eight accounting metrics. Considering only sale and income metrics, the *Performance Pay* is on average 2% for CEOs and top executives. These results are similar for only S&P-500 firms and peer firms in the same industry. Regarding the *Value Premium,* the average of the eight accounting metrics is 29%, 28%, 27% when we use the percentiles p85(p15), quintiles and quartiles, respectively. Finally, in 49% of the firm-metric-year observations the functional background is consistent with the accounting metric of interest (i.e the functional background is output oriented and the accounting metrics is sales growth) and firms only provide aligned incentives in 23% of the firm-metric-year observations.

3.5 Empirical Results

3.5.1 CEO Compensation Design

We begin our empirical analysis by testing hypothesis 1 and we present the results in Table 3.2 Panel A. According to hypothesis 1, we should expect a positive sign for the coefficient associated with our main independent variable, *Value Premium*. Columns (1)-(3) show the results for the CEO sample. We can see a positive coefficient on the variable *Value Premium* in the three columns. Also, for all the cutoffs used (p85(p15), quintiles and quartiles), the coefficients are statistically significant. Moreover, the coefficients increase monotonically from 0.003 to 0.006. These results suggest that firms design CEO compensation following investor demand in the previous period with respect to the two business strategies, growth and profit. The results are also consistent using the average compensation of the top 5 executives in the firm (Columns (4)-(6)). However, the coefficients are smaller as compared to the CEO results (quintile and quartile). In terms of economic magnitude, one standard deviation increase in the *Value Premium* increases on average 0.11%-0.18% (0.11%-0.15%) the performance pay of CEOs (top executives). Considering that in our sample the performance pay of the eight accounting metrics is on average 1%, the effect of investor demand is economically significant.

Given that the sale and income goals represent the higher fraction of the total compensation tied to those accounting metrics, In Panel B we show the results associated with the *Value Premium* variables only considering the sale and income accounting metrics (Sales, EPS, Operating Income and ROE). We use this subsample because those metrics are highly employed by firms in terms of number of grants and as a percentage of the total compensation. The results are consistent with Panel A. However, the coefficients associated with our main variable are larger for both the CEO and top executive samples, 0.005-0.009 and 0.005-0.008, respectively. In terms of economic magnitude, one standard deviation increase in the *Value Premium* increases on average 0.19%-0.28% (0.19%-0.25%) the performance pay of CEOs (top executives). Again, considering that in our sample the performance pay of sale and income metrics is on average 2%, the effect of investor demand is economically significant. Overall, our analysis shows that boards of directors tend to link executive compensation to performance metrics according to investor demand, and they do so to encourage executives to focus their efforts on those metrics and increase the current market value of the firm.

In addition, the positive and significant coefficient associated with the variable *Peer Pay,* in all the columns of Panels A and B, suggests that peer compensation (in the same industry) has a direct effect on the compensation of specific firms. Thus, these results shed light on the influence of market preferences and the peers' executive compensation on the individual firm executive compensation design. Moreover, the coefficient of the variable *Stock Return* is negative and significant. Firms tend to link executive compensation to accounting performance metrics when stock price performance is poor.

Regarding corporate governance metrics, we find that the variables *Power Index, Independent Director Ratio* and the *Entrenchment Index* are statistically significant and have negative and positive signs, respectively. Powerful CEOs tend to have a lower fraction of their compensation tied to accounting metrics. CEOs with higher *Performance Pay* have to work harder (more effort) to achieve the accounting goals. That is because the accounting goals are easy to verify, which induces CEOs to increase their efforts. On the other hand, *Independent Director Ratio and Entrenchment Index* (both dummy variables) are proxy variables that captures the shareholders' rights.[8] Hence, our results are consistent, firms with higher (lower) *Independent Director Ratio (Entrenchment Index)* have a higher fraction of the CEO compensation tied to accounting metrics.

We perform additional cross-sectional tests related to corporate governance characteristics. Specifically we look at the interaction between our main variable, *Value Premium,* and the *Power Index* and *Entrenchment Index.* Given that firms cater to investor demand, higher *Value Premium* increase the *Performance Pay.* However, we expect that powerful CEOs will avoid that situation having a *Performance Pay* less sensitive to investor demand. As opposed to firm with stronger shareholders rights, where those can increase the shareholders' wealth when firms follow market preferences for certain accounting metrics. Therefore , we expect that the coefficient associated with the interaction term *Value Premium x Power Index (Value Premium x Independent Director Ratio and Value Premium x Entrenchment Index)* should be negative (positive).

Table 3.3 provides the results of the interaction between *Value Premium* and corporate governance characteristics. We only find the expected results for the interaction term *Value Premium x Power Index,* the coefficient is negative and statistically significant (Columns (1)-(3)). Firms with powerful CEOs are less willing to cater to investor demand and increase the *Performance Pay* according to market preferences.

Finally, for robustness we change the specification of the equation (5). Instead of using firm characteristics contained in the vector Z_{it}, we exploit the fact that we have an extra dimension in our panel data, which is the accounting metric k, and we control for firm-year fixed effects. In other words, in a given year we have more than one observation for each firm, then we have more degrees of freedom (number of firms (F) $\times$ number of years (T) $\times$ number of accounting metrics (K)=F$\times$T$\times$K) than parameters if we incorporate firm-year

[8] *Entrenchment Index* is inversely related to the strength of shareholder rights

fixed effects. Therefore, we can control for firm-year fixed effects and estimate the coefficient associated with *Value Premium.* Doing so, we control for any time varying firm characteristics. This specification is more demanding than just controlling for observed characteristics (Z_{it}). However, we can only estimate the parameters that have cross-sectional variation within firm-year such as *Value Premium, Peer Pay* and *Industry Performance.* Additionally, we cluster at firm level.

As we expected, in Table 3.4 we show that the explanatory power of the *Value Premium* is lower as compared to the results in Table 3.2. With respect to the CEO subsample, in column (1) we can see that the coefficient of *Value Premium* variable (employing the percentiles p(85) and p(15) as cutoffs) is no longer statistically different from zero, when we consider the eight and only sale and income metrics (Column (1) in Panels A and B). In columns (2) and (5), for of case of the *Value Premium* using quintiles (cutoffs p80 and p20), the coefficients are still statistically significant at 5%, but in Panel B we can see that the effect is only statistically significant at 10% level when we only consider CEOs (Column (2)). However, the *Value Premium* using quartiles is still statistically different from zero at 1% level for both CEO and top executive subsamples and using the eight and only sale and income accounting metrics (Columns (3) and (6)). Remarkably, all the coefficients are larger than those found in Table 3.2, which also implies a higher economic magnitudes. Focusing on quartiles, an increase in one standard deviation of the *Value Premium* rises the *Performance Pay* by 0.24% (0.39%) for the eight metrics (sale and income metrics) sample. Overall, our results are robust to different specifications and the strongest effect is found using the *Value Premium* based on the percentiles p25 and p75 as cutoffs.

3.5.2 CEO Compensation and Functional Background

Table 3.5 presents the results that combine CEO *Performance Pay* and *Functional Background* as important determinants of firm performance (hypothesis 2). In panel A, we use as control variables *Market-to-Book ratio*, *Size* and *Ind. Performance* and we can see that the coefficient associated with the *Functional Background* is positive and statistically different from zero for the different horizons in which we measure firm performance (average performance for the next 1, 2 and 3 years). In addition, using the eight metrics (columns (1)-(3)), we show that the *Functional Background* is more important in the long-run (3 years) as compared to the short-run (1 year). In fact, firms whose CEOs possess the *Functional Background* consistent with the accounting metrics associated with either exploration or exploitation activities have on average 3.1%, 5.0% and 8% higher performance in the short-, medium- and long-run, respectively. Moreover, when we only consider the five most frequently employed metrics (EPS, Sales, Operating Income, Earnings and EBITDA), the effect of *Functional Background* is stronger, firms have on average 3.7%, 6.0% and 9.6% better performance. In addition, the effect of Functional Background are robust even after controlling for firm-year fixed effects (Panel B). It is important to highlight that the average performance is based on the eight accounting metrics used in this study. Unfortunately, we are no able to isolate the performance associated with growth- or profit-oriented activities. We only can show the average performance at firm level.

With respect to the *Performance Pay* measure, the results are in line with our hypothesis (although the statistical significance is low). In Panel A, columns (4) and (5), we find a positive effect of *Performance Pay* on firm performance and the effect is mainly concentrated in the short-run and medium-run. Moreover, the coefficients associated with *Performance Pay* are consistently larger than the coefficients of the *Functional Background*. However, in unreported tests we find that the two coefficients are not statistically distinguishable. However, the *Performance Pay* has low explanatory power (Panel A), we only find stronger results in the medium-term and when we employ just the five common used metrics. In terms of economic magnitude, an increase in the *Performance Pay* by 6% (one standard deviation) improves the performance of firms by 1% in the medium-run. When we consider the eight metrics the results work poorly. In fact, the effect of *Performance Pay* is just statistically different from zero at 10% level and only in the short-term. In addition, In Panel B, when we include firm-year fixed effect, the coefficients associated with *Performance Pay* become less important in explaining firm performance. These surprising results shed light on the way that CEOs respond to incentives and how CEO characteristics might affect the effectiveness of linking compensation to accounting goals. For that reason, in the following test, we show that the *Performance Pay* has a different impact on firm performance depending on the tenure of the CEO.

In our sample the average annual compensation of CEOs is around 8 million dollars which is almost twice the average annual compensation of other top executives. Hence, executives who become CEOs suffer a large positive shock in their compensation. We argue that the effect of performance pay on accounting goals should be higher for recently appointed CEOs. The expected increase in compensation that is conditional on meeting the targets exerts more influence on CEO effort. In contrast, CEO tenure is positively associated with total compensation (Hill and Phan (1991)), for that reason the incentives associated with performance goals for older CEOs are less appealing due to the wealth effect. The percentage of the total compensation tied to accounting metrics becomes a small fraction of the CEOs' total wealth when they have held to the job for a long time. In addition, if the forced turnover is more likely for CEOs with lower tenure, then new CEOs have more incentives to meet the accounting goals to keep their job. In fact, Bennett, Bettis, Gopalan, and Milbourn (2015) show that the probability of forced turnovers is higher when CEOs miss the accounting targets and the tenure is negatively associated with forced turnovers.

Having said that, we look deeper into the effect *Performance Pay* on firm performance and we split the sample in two, new and older CEOs (Yim (2013)). We define new CEOs as executives who were appointed to the position within the last two years. And, we define older CEOs as having tenure of more than two years.

Table 3.6 Panel A displays the results of new and older CEOs using the eight accounting metrics. In columns (1) and (3), *Performance Pay* has a highly significant positive effect on firm performance mainly for new CEOs in the short- and medium-run. But more importantly, the effect on firm performance considering older CEOs is not statistically significant for the three time horizon (columns (2), (4) and (6)). However, the *Functional Background* is still an important determinant of firm performance for the medium- and long-term in the case of older CEOs and for the three horizons when we look at new CEOs.

Panel B shows the results of new and older CEOs using the five most frequent accounting metrics. As opposed to the previous evidence presented in Panel A, *Performance Pay* has an important and positive effect on firm performance for recently appointed CEOs in the short- and medium-run. In terms of economic magnitudes, a one standard increase (7%) in the *Performance Pay* improves firm performance by 1.5%, 2.7% and 3.3% in the short-, medium- and long-run, respectively. For the older CEOs subsample, *Performance Pay* does not matter much in explaining firm performance. More importantly, our analysis shows that *Performance Pay* has a long lasting effect on firm performance for new CEOs. Overall, these result suggest that linking executive compensation to accounting goals help to improve firms performance only when CEOs are new in their jobs.

3.5.3 Aligned Incentives

Table 3.7 displays the results regarding *Aligned Incentives*. We combine the functional background of CEOs and their compensation structure to test whether firms that provide a compensation package consistent with the functional background of the CEO outperform firms with misaligned incentives. Thus, our main variable of interest is *Aligned Incentives,* which takes the value of 1 in two cases. First, the CEO has an output-oriented functional background and the firm ties her compensation to sales growth targets. The second case is when the CEO has a profit-oriented functional background and her compensation package is mainly determined by profitability goals.

When we consider the full sample, there is no effect of *Aligned Incentives* on firm performance for the three time horizons. Given our previous results regarding new and older CEOs we argue that the effect of *Aligned Incentives* should be stronger when we only consider new CEOs. Thus, we follow the methodology of the previous table and split the sample in two. Doing so, the results suggest that *Aligned Incentives* are more important for recently appointed CEOs (less than two years). Using the eight accounting metrics (Panel A), we find a positive relation between *Aligned Incentives* and firm performance in the short and long-run. In columns (2), (4) and (6), we show that firms with *Aligned Incentives* outperform firms with misaligned incentives by 6.4%, 11.3% and 11.2% in the short-, medium- and long-run, respectively. In addition, the coefficients of *Aligned Incentives* are larger when we only consider the five most frequently employed accounting metrics to define performance goals. Firms with *Aligned Incentives* outperform firms with misaligned incentives by 8.3%, 12.7% and 12.4% in the short-, medium- and long-run (Columns (2), (4) and (6)), respectively.

Finally, in Table 3.8 we show that the effect of *Aligned Incentives* is robust to firm-year fixed effects. Considering only new CEOs and the eight accounting metrics, we report that the coefficient associated with *Aligned Incentives* is still positive and statistically different from zero in the short-, medium and long-run. Remarkably, the coefficients are larger as compared to those in Table 3.7; firms with *Aligned Incentives* outperform firms with misaligned incentives by 10.9%, 14.4% and 13.1% in the short-, medium- and long-run, respectively. Also the results are robust using only the five most frequently employed metrics, expect for the long-run. In panel B, we show that economic impact of *Aligned Incentives* is 11.6% and 14% in the short-, and medium-run, respectively. Overall, our results suggest that *Performance Pay* makes a difference only in new CEOs, but more importantly, firms can achieve a better performance when they bring in a new leader and design a compensation plan consistent with the functional background of the incoming CEO. The last result contributes to the literature of executive compensation and CEO succession by showing that together, functional background and incentives plans, are crucial to have successful firms in the long-run.

3.6 Conclusion

We use a comprehensive dataset containing information on the accounting performance goals employed by firms to provide evidence that firms design executive compensation to cater to investor demand. We show that boards of directors tie the compensation of their executives to accounting metrics preferred by investors. We create the *Value Premium* variable, which is a proxy for investor demand, to show that investor preferences in the previous year have a positive effect on the executive performance pay in the current year.

In addition, we show that both performance pay and functional background are important determinants of firm performance in the short-, medium- and long-run. But the effect of performance pay is mainly concentrated in new CEOs and the functional background has a long-lasting effect on firm performance for both new and older CEOs. Moreover, for recently appointed CEOs, we provide evidence that firms obtain better performance when they design compensation plans consistent with the CEO's functional background. Our results provide evidence that the literature of executive compensation and CEO succession are highly related by showing that together, functional background of new leaders and incentives plans, are crucial to have successful firms in the long-run.

Finally, after the new SEC rules in 2006 there are several open questions regarding executive contracts. This study contributes to the discussion of how firms design compensation plans for their executives and how these designs impact firm performance.

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3.8 Appendix C: Variable definitions

- *Aligned Incentives*: Dummy variable that takes the value of 1 when a firm has CEO performance pay focused on growth (profit) performance and the CEO functional background is growth (profit) oriented, zero otherwise.
- Cash Flows: Operating Income minus Accruals ($\Delta CA - \Delta CashandEq. - \Delta CL - \Delta DebtinCL - DP$). Cash Flow/TA: Cash flows to total assets
- Earnings: net income.
- EBIT: Earnings before interest and taxes.
- EBITDA: Earnings before interest, taxes, depreciation and amortization.
- Entrenchment index is the Bebchuk et al. (2009) entrenchment index.
- EPS: Earnings per share.
- Percentage of Independent Directors: fraction of independent directors on the firm's board.
- Industry Performance: Average performance (growth rates) of the firm's peers in the same industry (two-digit SIC code) with respect to the eight metrics (Sales growth, Earnings growth, Operating income growth, Cash flows growth, EBIT growth, EBITDA growth, ROE growth, and EPS growth).
- Market-to-Book: Market value of assets (market value of common shares plus preferred stock liquidating value plus short and long debt minus deferred taxes and investment tax credit) divided by the total book asset value.
- Operating Income: Sales minus cost of goods sold and depreciation
- *Peer Pay:* peer executive compensation linked to the eight performance metrics in the same three-digit SIC code industry classification.
- *Performance Pay*: Vector that contains the fraction of total compensation (which is the sum of annual salary, bonus, present value of stock awards, present value of stock option awards, other annual compensation, long-term incentive payouts, and other cash payouts) linked to the accounting performance metrics.
- Power Index (Morse et al. (2011)): Variable with a range from 1 to 3 depending on the number of titles that a CEO holds in the firm. If the CEO is the president of the firm and also the chairman of the board the index is equal to 3. If the CEO is only the chairman of the board the index is equal to 2. Finally, if the CEO is not the chairman of the firm the index is equal to 1.
- ROE: Return on Equity (Net income divided by common equity)
- Sales Growth: Change in sales between the previous year and the current year divided by the sales of previous year

- Size: Natural logarithm of Total assets.
- Spread: Average daily stock bid-ask spread.
- Stock Return: Annual stock return.
- Tenure is the tenure of the CEO.
- *Value Premium*: Natural logarithmic difference of the average market-to-book ratios between firms with higher accounting performance (in the top of the distribution) versus firms with lower accounting performance (in the bottom of the distribution). For each year and two-digit SIC code industry classification we rank the firms based on the firm performance with respect to the eight accounting metrics.

3.9 Tables

Table 3.1: Summary Statistics

This table presents the summary statistics for the performance pay, the *Value Premium* variable, functional background and firm characteristics. Panel A shows the summary statistics for the fraction of the total compensation tied to accounting metrics. Panel B displays the statistics for *Value Premium* variable with respect to the eight accounting metrics. Panel C and D provide the information regarding CEO characteristics, peer performance pay and control variables at firm level. The eight accounting metrics are: EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT and the five most frequently used accounting metrics by firms are: EPS, Sales, Operating Income, Earnings, EBITDA. All variables used in the regression analysis are winsorized at the 1st and 99th percentile.

Panel A: Performance Pay. Fraction of total compensation tied to performance metrics										
	CEO					Top Executives				
	N	Mean	SD	Min	Max	N	Mean	SD	Min	Max
Sales	4460	0.02	0.06	0	0.36	4414	0.02	0.05	0	0.31
Earnings	4460	0.01	0.04	0	0.25	4414	0.01	0.04	0	0.24
Operating Income	4460	0.02	0.07	0	0.41	4414	0.02	0.06	0	0.34
Cash Flow	4460	0.01	0.04	0	0.28	4414	0.01	0.03	0	0.21
EBIT	4460	0	0.02	0	0.14	4414	0	0.02	0	0.12
EBITDA	4460	0.01	0.04	0	0.31	4414	0.01	0.04	0	0.28
ROE	4460	0	0.02	0	0.15	4414	0	0.02	0	0.13
EPS	4460	0.04	0.1	0	0.51	4414	0.03	0.08	0	0.44
Profit (Total)	4460	0.10	0.13	0	0.8	4460	0.08	0.11	0	0.61

Panel B: Value Premium						
Growth rate	N	Mean	SD	P25	Median	P75
Sales_p85 vs. p15	4366	0.5	0.4	0.26	0.52	0.77
Sales_quintile	4366	0.49	0.34	0.28	0.48	0.72
Sales_quartile	4366	0.46	0.32	0.26	0.45	0.65
Earnings_p85 vs. p15	4366	0.29	0.32	0.08	0.28	0.52
Earnings_quintile	4366	0.26	0.31	0.06	0.26	0.45
Earnings_quartile	4366	0.25	0.28	0.06	0.23	0.44
Op. Income_p85 vs. p15	4366	0.32	0.33	0.1	0.32	0.51
Op. Income_quintile	4366	0.31	0.31	0.1	0.3	0.48
Op. Income_quartile	4366	0.3	0.28	0.12	0.28	0.49
Cash Flow_p85 vs. p15	3660	0.13	0.31	-0.05	0.14	0.3
Cash Flow_quintile	3660	0.16	0.28	0.01	0.17	0.36
Cash Flow_quartile	3660	0.16	0.25	0	0.14	0.29
EBIT_p85 vs. p15	4366	0.31	0.33	0.11	0.3	0.52
EBIT_quintile	4366	0.3	0.3	0.11	0.29	0.48
EBIT_quartile	4366	0.29	0.29	0.12	0.28	0.46
EBITDA_p85 vs. p15	4366	0.32	0.33	0.1	0.32	0.51
EBITDA_quintile	4366	0.31	0.31	0.1	0.3	0.48
EBITDA_quartile	4366	0.3	0.28	0.12	0.28	0.49
ROE_p85 vs. p15	4366	0.21	0.34	0.03	0.21	0.39
ROE_quintile	4366	0.21	0.31	0	0.23	0.39
ROE_quartile	4366	0.2	0.29	0.01	0.2	0.36
EPS_p85 vs. p15	4366	0.21	0.32	0.03	0.24	0.41
EPS_quintile	4366	0.21	0.3	0.02	0.23	0.4
EPS_quartile	4366	0.21	0.28	0.04	0.2	0.41

Panel C: Full Sample	Eight Metrics						Only Sale and Income Metrics					
	N	Mean	SD	P25	Median	P75	N	Mean	SD	P25	Median	P75
Performance pay	22704	0.01	0.06	0.00	0.00	0.00	11352	0.02	0.06	0.00	0.00	0.00
Performance pay (Top Executives)	22664	0.01	0.05	0.00	0.00	0.00	11332	0.02	0.05	0.00	0.00	0.00
Peer pay	22704	0.01	0.03	0.00	0.00	0.01	11352	0.02	0.04	0.00	0.00	0.02
Peer pay (Top Executives)	22704	0.01	0.03	0.00	0.00	0.01	11352	0.01	0.03	0.00	0.00	0.02
Value premium-p85 vs. p15	22274	0.29	0.35	0.05	0.28	0.50	11184	0.30	0.37	0.06	0.31	0.54
Value premium-quintile	22274	0.28	0.32	0.07	0.27	0.48	11184	0.29	0.34	0.06	0.28	0.51
Value premium-quartile	22274	0.27	0.30	0.08	0.25	0.46	11184	0.28	0.31	0.06	0.26	0.48
Stock Return	22704	0.13	0.47	-0.16	0.09	0.33	11352	0.13	0.47	-0.16	0.09	0.33
Sales Growth	22704	0.08	0.20	-0.02	0.07	0.15	11352	0.08	0.20	-0.02	0.07	0.15
Cashflow/TA	21976	0.15	0.08	0.10	0.14	0.19	10988	0.15	0.08	0.10	0.14	0.19
Spread	22656	0.00	0.00	0.00	0.00	0.00	11328	0.00	0.00	0.00	0.00	0.00
Size	22704	8.52	1.32	7.64	8.40	9.32	11352	8.52	1.32	7.64	8.40	9.32
Market-to-Book	22704	1.53	1.00	0.85	1.25	1.87	11352	1.53	1.00	0.85	1.25	1.87
Industry Performance	22669	-0.02	0.84	-0.31	0.01	0.33	11352	-0.03	0.90	-0.35	0.06	0.39
Stock Ownership (CEO)	22424	1.37	3.48	0.03	0.32	1.21	11212	1.37	3.48	0.03	0.32	1.21
Tenure (CEO)	22368	7.45	6.26	3.21	5.75	9.58	11184	7.45	6.26	3.21	5.75	9.58
Age (CEO)	22416	55.42	6.37	51.00	56.00	60.00	11208	55.42	6.37	51.00	56.00	60.00
Power Index	22424	1.86	0.82	1.00	2.00	3.00	11212	1.86	0.82	1.00	2.00	3.00
Independent Director Ratio (Dummy)	22704	0.37	0.48	0.00	0.00	1.00	11352	0.37	0.48	0.00	0.00	1.00
Entrenchment Index (Dummy)	22704	0.55	0.50	0.00	1.00	1.00	11352	0.55	0.50	0.00	1.00	1.00

Panel D: SP-500 Sample	Eight Metrics						Five Frequently Used Metrics					
Performance pay	15736	0.01	0.06	0.00	0.00	0.00	9835	0.02	0.07	0.00	0.00	0.00
Aligned Incentives	15736	0.23	0.42	0.00	0.00	0.00	9835	0.23	0.42	0.00	0.00	0.00
Background	15736	0.49	0.50	0.00	0.00	1.00	9835	0.50	0.50	0.00	1.00	1.00
Size	15736	9.31	1.17	8.47	9.15	10.15	9835	9.31	1.17	8.47	9.15	10.15
Market-to-Book	15736	1.70	1.07	0.94	1.39	2.10	9835	1.70	1.07	0.94	1.39	2.10
Performance 1yrs.	15660	-0.01	0.28	-0.06	-0.02	0.01	9830	-0.01	0.34	-0.06	-0.02	0.02
Performance 2yrs.	13247	-0.05	0.49	-0.25	-0.09	0.05	8223	-0.05	0.54	-0.27	-0.12	0.05
Performance 3yrs.	8604	-0.03	0.59	-0.30	-0.09	0.08	5313	-0.04	0.61	-0.32	-0.13	0.09
Ind. Performance 1yr.	15736	-0.01	0.77	-0.24	0.02	0.31	9835	0.00	0.83	-0.25	0.04	0.37
Ind. Performance 2yr.	15181	-0.02	0.75	-0.37	-0.06	0.27	9488	-0.01	0.83	-0.42	-0.08	0.34
Ind. Performance 3yr.	13067	0.00	0.77	-0.39	0.01	0.33	8165	0.00	0.83	-0.45	0.02	0.36

Table 3.2: Executive Compensation and Catering Incentives

The table presents the results of the effect of investor demand on executive compensation. The dependent variable is *Performance Pay,* which is the faction of the total compensation tied to an specific accounting metric. Our main independent variable is the *Value Premium,* which measures the market's preferences for an specific accounting metric. Moreover, we have two samples: (1) CEO and (2) Top executive compensation. Panel A shows the results using the eight accounting metrics (EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT) and Panel B considers only sale and income accounting metrics used by firms (Sales, EPS, Earnings and ROE). The control variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and the standard errors are clustered at firm-year level. The constant is not reported. See Appendix C for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Table A: Eight Metrics						
	CEO			Top Executives		
	(1)	(2)	(3)	(4)	(5)	(6)
Value Premium-p85(p15)	.003			.003		
	(.001)**			(.001)***		
Value Premium-quintile		.005			.004	
		(.002)***			(.001)***	
Value Premium-quartile			.006			.005
			(.002)***			(.001)***
Peer pay	.233	.232	.232	.207	.206	.205
	(.020)***	(.020)***	(.020)***	(.019)***	(.018)***	(.018)***
Stock Own.	.00007	.00006	.00007			
	(.0002)	(.0002)	(.0002)			
Tenure	.00007	.00007	.00007			
	(.0002)	(.0002)	(.0002)			
Power Index	-.001	-.001	-.001	-.0008	-.0008	-.0009
	(.0007)**	(.0007)**	(.0007)**	(.0006)	(.0006)	(.0006)
Independent Director Ratio	.002	.002	.002	.001	.001	.001
	(.0008)**	(.0008)**	(.0008)**	(.0006)*	(.0006)*	(.0006)*
Entrenchment Index	.003	.003	.003	.002	.002	.002
	(.0009)***	(.0009)***	(.0009)***	(.0007)**	(.0007)**	(.0007)**
Stock return	-.003	-.003	-.003	-.002	-.002	-.002
	(.0007)***	(.0007)***	(.0007)***	(.0006)***	(.0006)***	(.0006)***
Sales growth	.0009	.0008	.0009	.002	.001	.002
	(.002)	(.002)	(.002)	(.001)	(.001)	(.001)
Cashflow/TA	.002	.002	.002	.005	.005	.005
	(.004)	(.004)	(.004)	(.004)	(.004)	(.004)
Spread	.930	.932	.925	.382	.384	.377
	(.483)*	(.483)*	(.483)*	(.328)	(.328)	(.328)
Size	.001	.001	.001	.002	.002	.002
	(.001)	(.001)	(.001)	(.001)*	(.001)	(.001)
Industry Performance	-.00007	-.0001	-.0001	-.0002	-.0003	-.0003
	(.0004)	(.0004)	(.0004)	(.0003)	(.0003)	(.0003)
Market-to-Book	.0007	.0007	.0008	.0006	.0006	.0007
	(.0008)	(.0008)	(.0008)	(.0006)	(.0006)	(.0006)
Obs.	21219	21219	21219	21227	21227	21227
R^2	.098	.098	.098	.099	.099	.099

Table B: Sale and income metrics

	CEO			Top Executives		
	(1)	(2)	(3)	(4)	(5)	(6)
Value Premium–p85(p15)	.005			.005		
	(.002)**			(.002)***		
Value Premium-quintile		.007			.006	
		(.002)***			(.002)***	
Value Premium-quartile			.009			.008
			(.002)***			(.002)***
Peer pay	.270	.270	.268	.235	.234	.233
	(.027)***	(.027)***	(.027)***	(.024)***	(.024)***	(.024)***
Stock Own.	.0001	.0001	.0001			
	(.0003)	(.0003)	(.0003)			
Tenure	.0003	.0003	.0003			
	(.0003)	(.0003)	(.0003)			
Power Index	-.003	-.003	-.003	-.001	-.001	-.001
	(.001)**	(.001)**	(.001)**	(.0009)	(.0009)	(.0009)
Independent Director Ratio	.002	.002	.002	.001	.001	.001
	(.001)**	(.001)**	(.001)**	(.001)	(.001)	(.001)
Entrenchment Index	.004	.004	.004	.003	.003	.003
	(.001)***	(.001)***	(.001)***	(.001)**	(.001)**	(.001)**
Stock return	-.002	-.002	-.002	-.002	-.002	-.002
	(.001)**	(.001)**	(.001)**	(.0009)**	(.0009)**	(.0009)**
Sales growth	-.002	-.002	-.002	-.002	-.002	-.002
	(.002)	(.002)	(.002)	(.002)	(.002)	(.002)
Cashflow/TA	-.005	-.005	-.005	-.004	-.004	-.004
	(.007)	(.007)	(.007)	(.006)	(.006)	(.006)
Spread	.712	.706	.688	.430	.426	.410
	(.716)	(.715)	(.714)	(.501)	(.500)	(.499)
Size	.003	.003	.003	.003	.003	.003
	(.002)	(.002)	(.002)	(.002)*	(.002)*	(.002)*
Market-to-Book	.0002	.0002	.00005	.00009	.00009	-2.89e-06
	(.0005)	(.0005)	(.0006)	(.0005)	(.0005)	(.0005)
Industry Performance	.0006	.0006	.0007	.0002	.0002	.0003
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Obs.	10632	10632	10632	10636	10636	10636
R^2	.187	.187	.187	.185	.185	.186

Table 3.3: Executive Compensation, Catering Incentives and Corporate Governance

The table presents the results of the effect of investor demand and corporate governance characteristics on CEO compensation. The dependent variable is *Performance Pay,* which is the fraction of the total compensation tied to an specific accounting metric. Our main independent variable is the *Value Premium,* which measures the market's preferences for an specific accounting metric. Panel A shows the results using the eight accounting metrics (Sales, Earnings, Operating income, Cash flows, EBIT, EBITDA, ROE and EPS) and Panel B considers only sale and income accounting metrics used by firms (Sales, EPS, Earnings and ROE). The control variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and the standard errors are clustered at firm-year level. See Appendix C for a complete variable definitions. The constant is not reported. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Table A: Eight Metrics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	P85(P15)	Quintile	Quartile	P85(P15)	Quintile	Quartile	P85(P15)	Quintile	Quartile
Value Premium (VP)	.011	.014	.018	.004	.006	.007	.003	.005	.005
	(.003)***	(.004)***	(.004)***	(.002)**	(.002)***	(.002)***	(.002)	(.002)**	(.002)**
VP x Power Index	-.005	-.005	-.006						
	(.001)***	(.002)***	(.002)***						
VP x Independent Directors				-.002	-.002	-.002			
				(.003)	(.003)	(.003)			
VP x Entrenchment Index							.0002	.0003	.001
							(.002)	(.003)	(.003)
Power Index	-.00008	.00007	.0002	-.001	-.001	-.001	-.001	-.001	-.001
	(.0008)	(.0008)	(.0008)	(.0007)**	(.0007)**	(.0007)**	(.0007)**	(.0007)**	(.0007)**
Independent Directors	.002	.001	.001	.002	.002	.002	.002	.002	.002
	(.0008)**	(.0008)**	(.0008)*	(.001)**	(.001)**	(.001)*	(.0008)**	(.0008)**	(.0008)**
Entrenchment Index	.003	.003	.003	.003	.003	.003	.002	.002	.002
	(.0009)***	(.0009)***	(.0009)***	(.0009)***	(.0009)***	(.0009)***	(.001)**	(.001)**	(.001)*
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	21219	21219	21219	21219	21219	21219	21219	21219	21219
R^2	.098	.098	.099	.098	.098	.098	.098	.098	.098

Table B: Sale and Income accounting metrics

	P85(P15)	Quintile	Quartile	P85(P15)	Quintile	Quartile	P85(P15)	Quintile	Quartile
Value Premium	.018	.019	.022	.006	.007	.009	.005	.008	.010
	(.005)***	(.006)***	(.006)***	(.002)**	(.002)***	(.003)***	(.003)*	(.003)**	(.003)***
VP x Power Index	-.007	-.006	-.007						
	(.002)***	(.002)***	(.003)***						
VP x Independent Directors				-.001	-.0006	-.0004			
				(.004)	(.005)	(.005)			
VP x Entrenchment Index							-.0007	-.0009	-.001
							(.004)	(.004)	(.004)
Power Index	-.0005	-.0007	-.0007	-.003	-.003	-.003	-.003	-.003	-.003
	(.001)	(.001)	(.001)	(.001)**	(.001)**	(.001)**	(.001)**	(.001)**	(.001)**
Independent Directors	.002	.002	.002	.003	.003	.003	.002	.002	.002
	(.001)*	(.001)*	(.001)*	(.002)	(.002)	(.002)	(.001)**	(.001)**	(.001)**
Entrenchment Index	.004	.004	.004	.004	.004	.004	.004	.004	.004
	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***	(.001)***	(.002)**	(.002)**	(.002)**
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10632	10632	10632	10632	10632	10632	10632	10632	10632
R^2	.188	.188	.188	.187	.187	.187	.187	.187	.187

Table 3.4: Executive Compensation and Catering Incentives: Robustness Test

The table presents the results of the effect of investor demand on executive compensation. The dependent variable is *Performance Pay,* which is the fraction of the total compensation tied to an specific accounting metric. Our main independent variable is the *Value Premium,* which measures the market's preferences for an specific accounting metric. Moreover, we have two samples: (1) CEO and (2) Top executive compensation. Panel A shows the results using the eight accounting metrics (EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT) and Panel B considers only sale and income accounting metrics used by firms (Sales, EPS, Earnings and ROE). The control variables are winsorized at the 1st and 99th percentile. All regressions include firm-year-fixed effects and the standard errors are clustered at firm level. The constant is not reported. See Appendix C for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Table A: Eight Metrics						
	CEO			Top Executives		
	(1)	(2)	(3)	(4)	(5)	(6)
	P85(P15)	Quintile	Quartile	P85(P15)	Quintile	Quartile
Value Premium	.004	.006	.008	.004	.006	.008
	(.003)	(.003)**	(.003)***	(.002)*	(.002)**	(.003)***
Peer pay	.242	.241	.240	.215	.214	.213
	(.034)***	(.034)***	(.034)***	(.031)***	(.031)***	(.031)***
Industry Performance	.0007	.0007	.0006	.0004	.0004	.0003
	(.0008)	(.0008)	(.0008)	(.0006)	(.0006)	(.0006)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	21219	21219	21219	21227	21227	21227
R^2	.136	.136	.136	.137	.137	.137

Table B: Sale and Income metrics						
	CEO			Top Executives		
	P85(P15)	Quintile	Quartile	P85(P15)	Quintile	Quartile
Value Premium	.007	.010	.013	.007	.009	.012
	(.004)	(.005)*	(.005)**	(.004)*	(.004)**	(.005)***
Peer pay	.290	.290	.287	.252	.251	.248
	(.050)***	(.050)***	(.050)***	(.046)***	(.046)***	(.046)***
Industry Performance	-.0007	-.0005	-.0008	-.0004	-.0002	-.0004
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10632	10632	10632	10636	10636	10636
R^2	.264	.265	.265	.259	.259	.26

Table 3.5: Performance Pay and Functional Background

The table presents the results of the effect of performance pay and functional background on firm performance. The dependent variable is *Firm Performance*. We measure the performance of firms using three horizons: short-term (1 year), medium-term (2 years) and long-term (3 years). $Firm\ Performance_{itk}^{t,t}$ is the accounting metric growth k in the current fiscal year (1 year). $Firm\ Performance_{itk}^{t,t+1}$ is the average growth between the current year and the next year (2 years). And $Firm\ Performance_{itk}^{t,t+2}$ is the average growth between the current year, the next year and the year after (3 years). Our two main independent variables are the *Functional Background* and *Performance Pay*. The dummy variable $Functional\ Background_{ikt}$ is the functional background of the CEO. *Performance Pay* is the fraction of the total compensation tied to an specific accounting metric. The five the most frequently used accounting metrics by firms are: EPS, Sales, Operating Income, Earnings and EBITDA. The control variables are winsorized at the 1st and 99th percentile. The control variable *Ind. Performance* is the performance of the industry (two-digit SIC code) for the same time period that appears on the top of each column. Panel A reports the results using as control variable firm characteristics and all regressions include firm fixed effects. In Panel B all regressions include firm-year fixed effects. The standard errors are clustered at firm level. The constant is not reported. See Appendix C for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A	Eight Metrics			Five Frequently Employed Metric		
Firm Performance	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
	(1)	(2)	(3)	(4)	(5)	(6)
Functional Background	.031	.050	.079	.037	.060	.096
	(.016)*	(.024)**	(.029)***	(.018)**	(.027)**	(.032)***
Performance pay	.076	.105	.078	.081	.165	.165
	(.045)*	(.074)	(.097)	(.049)	(.083)**	(.111)
Market-to-Book	.034	.086	.051	.050	.101	.059
	(.008)***	(.022)***	(.028)*	(.012)***	(.027)***	(.034)*
Size	.054	-.032	-.197	.083	-.014	-.205
	(.018)***	(.063)	(.099)**	(.027)***	(.075)	(.120)*
Ind. Performance	.116	.233	.249	.144	.251	.272
	(.007)***	(.021)***	(.028)***	(.009)***	(.023)***	(.033)***
Obs.	15660	13247	10799	9830	8223	6676
R^2	.144	.242	.279	.2	.288	.336

Panel B	Eight Metrics			Five Frequently Employed Metric		
Firm Performance	1 Year	2 Years	3 Years	1 Year	2 Years	3 Years
Functional Background	.042	.066	.084	.044	.072	.096
	(.021)**	(.028)**	(.034)**	(.022)**	(.030)**	(.036)***
Performance pay	.083	.077	.026	.099	.143	.112
	(.048)*	(.070)	(.093)	(.057)*	(.085)*	(.116)
Ind. Performance	.166	.230	.235	.222	.262	.284
	(.011)***	(.020)***	(.031)***	(.016)***	(.030)***	(.047)***
Firm-Year F.E	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15660	13247	10799	9830	8223	6676
R^2	.284	.505	.5	.376	.588	.592

Table 3.6: Performance Pay and Functional Background: CEO Tenure

The table presents the results of the effect of performance pay and functional background on firm performance. The dependent variable is *Firm Performance*. We measure the performance of firms using three horizons: short-term (1 year), medium-term (2 years) and long-term (3 years). $Firm\ Performance_{itk}^{t,t}$ is the accounting metric growth k in the current fiscal year (1 year). $Firm\ Performance_{itk}^{t,t+1}$ is the average growth between the current year and the next year (2 years). And $Firm\ Performance_{itk}^{t,t+2}$ is the average growth between the current year, the next year and the year after (3 years). Our two main independent variables are the *Functional Background* and *Performance Pay*. The dummy variable $Functional\ Background_{ikt}$ is the functional background of the CEO. *Performance Pay* is the fraction of the total compensation tied to an specific accounting metric. We split the sample in two: (1) New CEOs (tenure≤2 years) and (2) Older CEOs (tenure>2 years). Also, Panel A shows the results using the eight accounting metrics (EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT) and Panel B considers the five most frequently used accounting metrics by firms (EPS, Sales, Operating Income, Earnings and EBITDA). The control variables are winsorized at the 1st and 99th percentile. All regressions include firm-year fixed effects and the standard errors are clustered at firm level. The control variable *Ind. Performance* is the performance of the industry (two-digit SIC code) for the same time period that appears on the top of each column. The constant is not reported. See Appendix C for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Firm Performance and recently appointed CEOs. Eight Metrics						
Firm Performance	1 Year		2 Year		3 Year	
	New CEO	Older CEO	New CEO	Older CEO	New CEO	Older CEO
	(1)	(2)	(3)	(4)	(5)	(6)
Functional Background	.056	.041	.100	.063	.103	.086
	(.033)*	(.025)	(.041)**	(.034)*	(.048)**	(.040)**
Performance pay	.174	.050	.226	.019	.206	-.057
	(.081)**	(.050)	(.115)**	(.078)	(.152)	(.107)
Ind. Performance	.133	.178	.188	.250	.195	.258
	(.018)***	(.013)***	(.031)***	(.024)***	(.033)***	(.040)***
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4311	10651	3685	8924	3007	7282
R^2	.266	.295	.454	.534	.455	.527

Panel B: Firm Performance and recently appointed CEOs. Five frequently employed metrics						
Firm Performance	1 Years		2 Years		3 Years	
	New CEO	Older CEO	New CEO	Older CEO	New CEO	Older CEO
	(1)	(2)	(3)	(4)	(5)	(6)
Functional Background	.057	.044	.100	.073	.108	.100
	(.035)*	(.026)*	(.044)**	(.035)**	(.052)**	(.041)**
Performance pay	.209	.055	.382	.058	.470	-.033
	(.091)**	(.062)	(.132)***	(.095)	(.175)***	(.136)
Ind. Performance	.173	.238	.201	.282	.223	.307
	(.029)***	(.019)***	(.044)***	(.037)***	(.052)***	(.057)***
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2710	6680	2294	5531	1863	4495
R^2	.354	.387	.544	.615	.562	.617

Table 3.7: Aligned Incentives and Firm Performance

The table presents the results of the effect of aligned incentives on firm performance. The dependent variable is *Firm Performance*. We measure the performance of firms using three horizons: (1) Short-term (1 year), (2) Medium-term (2 years) and (3) Long-term (3 years). $Firm\ Performance_{itk}^{t,t}$ is the accounting metric growth k in the current fiscal year (1 year). $Firm\ Performance_{itk}^{t,t+1}$ is the average growth between the current year and the next year (2 years). And $Firm\ Performance_{itk}^{t,t+2}$ is the average growth between the current year, the next year and the year after (3 years). Our main independent variables is *Aligned Incentives*, which *is* a dummy variable that takes the value of 1 when a firm has CEO performance pay focused on growth (profit) performance and the CEO functional background is growth (profit) oriented and zero otherwise. We split the sample in two: (1) New CEOs (tenure≤2 years) and (2) Older CEOs (tenure>2 years). Panel A shows the results using the eight accounting metrics (EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT) and Panel B considers the five most frequently used accounting metrics by firms (EPS, Sales, Operating Income, Earnings and EBITDA). The control variables are winsorized at the 1st and 99th percentile. All regressions include firm and year fixed effects and the standard errors are clustered at firm level. The control variable *Ind. Performance* is the performance of the industry (two-digit SIC code) for the same time period that appears on the top of each column. The constant is not reported. See Appendix C for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Eight Metrics

Firm Performance	1 Year			2 Years			3 Years		
	Full Sample	New CEO	Older CEO	Full Sample	New CEO	Older CEO	Full Sample	New CEO	Older CEO
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Aligned Incentives	.016	.064	.011	.007	.113	-.003	.021	.112	.007
	(.015)	(.031)**	(.021)	(.027)	(.044)***	(.037)	(.032)	(.055)**	(.047)
Market-to-Book	.033	.042	.041	.086	.105	.104	.052	.104	.056
	(.008)***	(.035)	(.007)***	(.022)***	(.055)*	(.025)***	(.027)*	(.054)*	(.025)**
Size	.055	-.002	.079	-.031	-.043	-.025	-.198	-.398	-.224
	(.018)***	(.046)	(.026)***	(.063)	(.136)	(.078)	(.099)**	(.160)**	(.123)*
Ind. Performance	.115	.096	.125	.233	.186	.257	.249	.198	.280
	(.007)***	(.015)***	(.008)***	(.021)***	(.031)***	(.025)***	(.028)***	(.026)***	(.037)***
Obs.	15660	4311	10651	13247	3685	8924	10799	3007	7282
R^2	.143	.144	.17	.24	.316	.305	.277	.369	.333

Panel B: Five frequently employed metrics

Firm Performance	1 Year			2 Years			3 Years		
	Full Sample	New CEO	Older CEO	Full Sample	New CEO	Older CEO	Full Sample	New CEO	Older CEO
Aligned Incentives	.023	.083	.010	.010	.127	-.014	.031	.124	.006
	(.019)	(.036)**	(.024)	(.031)	(.051)**	(.040)	(.038)	(.064)*	(.053)
Market-to-Book	.050	.067	.057	.101	.138	.117	.060	.119	.061
	(.012)***	(.046)	(.010)***	(.027)***	(.066)**	(.031)***	(.034)*	(.073)	(.032)*
Size	.084	-.016	.118	-.013	-.056	.019	-.206	-.447	-.194
	(.027)***	(.067)	(.038)***	(.075)	(.180)	(.096)	(.121)*	(.220)**	(.156)
Ind. Performance	.143	.113	.156	.251	.190	.276	.271	.209	.310
	(.009)***	(.020)***	(.010)***	(.023)***	(.035)***	(.028)***	(.033)***	(.032)***	(.043)***
Obs.	9830	2710	6680	8223	2294	5531	6676	1863	4495
R^2	.198	.202	.231	.285	.374	.357	.332	.435	.399

Table 3.8: Aligned Incentives: Robustness Test

The table presents the results of the effect of aligned incentives on firm performance. The dependent variable is *Firm Performance*. We measure the performance of firms using three horizons: (1) Short-term (1 year), (2) Medium-term (2 years) and (3) Long-term (3 years). $Firm\ Performance_{itk}^{t,t}$ is the accounting metric growth k in the current fiscal year (1 year). $Firm\ Performance_{itk}^{t,t+1}$ is the average growth between the current year and the next year (2 years). And $Firm\ Performance_{itk}^{t,t+2}$ is the average growth between the current year, the next year and the year after (3 years). Our main independent variables is *Aligned Incentives, which is* a dummy variable that takes the value of 1 when a firm has CEO performance pay focused on growth (profit) performance and the CEO functional background is growth (profit) oriented and zero otherwise. We split the sample in two: (1) New CEOs (tenure$\leq$2 years) and (2) Older CEOs (tenure>2 years). Panel A shows the results using the eight accounting metrics (EPS, Sales, Operating Income, Earnings, EBITDA, Cash flow, ROE and EBIT) and Panel B considers the five most frequently used accounting metrics by firms (EPS, Sales, Operating Income, Earnings and EBITDA). The control variables are winsorized at the 1st and 99th percentile. All regressions include firm-year fixed effects and the standard errors are clustered at firm level. The control variable *Ind. Performance* is the performance of the industry (two-digit SIC code) for the same time period that appears on the top of each column. The constant is not reported. See Appendix C for a complete variable definitions. Statistical significance at the 10%, 5% and 1% levels is denoted by *, ** and ***, respectively. Standard errors are in parenthesis.

Panel A: Eight Metrics

Firm Performance	1 Year		2 Years		3 Years	
	New CEO	Older CEO	New CEO	Older CEO	New CEO	Older CEO
	(1)	(2)	(3)	(4)	(5)	(6)
Aligned Incentives	.109	.004	.144	-.021	.131	-.008
	(.049)**	(.039)	(.063)**	(.054)	(.073)*	(.065)
Ind. Performance	.132	.178	.187	.250	.193	.258
	(.018)***	(.013)***	(.031)***	(.024)***	(.033)***	(.040)***
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4311	10651	3685	8924	3007	7282
R^2	.268	.293	.453	.532	.454	.525

Panel B: Five frequently employed metrics

Firm Performance	1 Year		2 Years		3 Years	
	New CEO	Older CEO	New CEO	Older CEO	New CEO	Older CEO
	(1)	(2)	(3)	(4)	(5)	(6)
Aligned Incentives	.116	.003	.140	-.025	.128	-.009
	(.052)**	(.040)	(.067)**	(.058)	(.080)	(.069)
Ind. Performance	.172	.237	.201	.283	.218	.307
	(.029)***	(.019)***	(.044)***	(.037)***	(.053)***	(.057)***
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2710	6680	2294	5531	1863	4495
R^2	.357	.385	.542	.612	.558	.614