Executive Compensation, Fat Cats, and Best Athletes

Jerry Kim a, Bruce Kogut a, Jae-Suk Yang a

aColumbia Business School, Columbia University, New York, USA

Abstract

The growth in the skewness of the distribution of income in the US dates from the past decades when the remuneration to chief executive officers (CEOs) has increased faster than the growth in firm size. An explanation for this rapid increase is the contagion of changes in social norms which, through a process of social comparison, propagates higher pay among corporate executives. By analyzing this increase in pay as a diffusion process, this paper compares three candidate explanations for contagion: director board interlocks, peer groups, and educational networks. Through coupling a Generalized Estimating Equations (GEE) model to endogeneity tests, the results indicate that contagion is evident for all three kinds of networks, but only the peer comparison clearly survives the selection tests. These results support the argument of DiPrete, Eirich, and Pittinsky (2010) that remuneration policies that are anchored on peer group comparisons propagate the diffusion of higher pay among chief executive officers in the US, though only with weak evidence for a ‘leapfrog’ effect. We show by an agent-based model that the process does not necessarily explode by an unsustainable aspirational bias because of the dampening of the contagion by CEO turnover and tenure effects. A key implication is that internet boom shifted upward the normative expectations of pay through social comparisons.

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1 Introduction

The stunning observation in the data on the distribution of income and wealth in the United States has been the reversal of a long trend starting in the 1930s of growing equality. By the 1980s, the share of income and wealth earned by the top 1% began an upward trend of growing inequality. Since an important element in this reversal is the increase in income to professional managers and lawyers, considerable attention among both academics and the public has been directed at the question of why executive pay rose so much in the past decades.

The chief executive officer (CEO) of a publicly-traded company is responsible for managing large and complex organizations. These responsibilities include setting the strategy of the firm, administering and leading a hierarchy of many employees, raising financing from capital markets, and deciding if to expand by growth or acquisition, or be acquired. These tasks are difficult and require skills and competence of well-educated and experienced individuals whose numbers are not abundant. Consequently, one of the principal functions of a board of directors is to reward CEOs sufficiently to attract and retain them. In the parlance of economics, these rewards must satisfy their “reservation” salary, which is the value an executive would require to accept the position rather than accept work elsewhere.

All economic theories of executive compensation accept this basic logic, and so stated, the logic is consistent with many sociological theories. However, there are large disagreements over the question if firms do not pay their executives more than this reservation wage. (We will argue later that this is set through social comparisons.) If labor markets for executives were competitive, markets would clear by ‘assortative matching’ through which more talented CEOs would work for firms that, because of the specific complexity of the required job, are willing to pay a premium for these talents; less talented CEOs would work for firms that are less demanding. In equilibrium, all CEOs are paid their reservation salary and ranked order by their talent. The evidence for this ‘best

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2 McCall and Percheski (2010) note that income shares held by the top percentile increased by 129% from 1979 to 2006, and 2007 marked the most unequal year since 1917 as measured by the share of income held by the top 0.01% (Piketty and Saez, 2006).

3 Kaplan and Rauh (2010) note that other earning groups, such as athletes, are members of the top 1% club and have seen faster income increases; nevertheless, managerial and professional pay dominates this bracket. Gordon and Dew-Becker (2008) estimate that top executives of the largest 1500 public firms earned 22% of income in the top .01% bracket; this percentage does not include hedge funds and private equity managers whose income grew much faster than that of public company managers, as noted by Kaplan and Rauh.
athlete’ argument is the simple correlation of the log market value of firms and the log salary of CEOs, which is easily apparent in the plot of the data (see, for example, Gabaix and Landier, 2008).

The appeal of this theory is that it is consistent with an important stylized fact, namely that since the 1970s average CEO pay has risen dramatically and the size of firms has also increased. A causal claim makes sense of this fact. Since firm size has increased, executive pay has as well. If we take this evidence at face value, the reported regression accounts still for less than 50%, which is interesting since the correlation is between two logged economic series that can be expected to be positive simply due to common trends. Moreover, as noted by Gordon and Dew-Becker (2008, 23), executive pay has in fact risen almost three times faster than firm growth in the past decades. While firm size (market value) and pay are correlated, it is statistically an open question as to why the latter has risen so much faster. 4

What other factors would then matter to the setting of compensation levels? There are several candidates. Bebchuk and Fried (2004) propose a theory of “rent extraction”, whereby salaries exceed the reservation salaries due to the power that CEOs exercise over their boards. Related to this idea is simply the observation of bad governance and the prevention of shareholders to monitor and effectively control their boards, leading to higher executive pay packages (Bertrand and Mullainathan, 2001). The same prediction results from the argument that growth in ‘pay for performance’ pay and better governance shifted risk onto executives, who required higher pay to compensate for the increased risk – their reservation salary increased due to increased risk. Apart from these theories of failed or better governance, other explanations suggest that there have been important structural changes in the US economy which have raised the premium for talent. This premium may be due to the increasing reliance on technology or increased internal complexity of large organizations (Garicano and Rossi-Hansberg, 2006).

These theories rely upon an observation of a structural change in the last decades. In analyzing a longer data series starting in 1936, Frydman and Saks (2010) find that the above theories are unlikely to explain this change. First, they find that while the level of pay up to the 1970s was lower, the relationship between performance and pay was already substantial. Thus, salary levels were lower but the incentives of pay for performance were already largely adopted in practice. Second, since governance practices are generally viewed as weaker prior to the 1990s, the evidence of lower salary levels contradicts the rent extraction story. Finally, Frydman and Saks propose that the subsequent

4 See Gordon and Dew-Becker, 2008, on the unrealistic prediction that arises from the Gabaix-Landier model given the empirical evidence on the elasticity of pay in reference to firm market value.
increase in salaries starting in the 1970s was too gradual to be consistent with theories that emphasize rapid technological change and the growing complexity of the executive job. Rather, they suggest, the change in the level of pay implies a change in the social norms that has shifted the reservation salary dramatically upward.

The challenge to the sociology of executive pay is to establish the mechanism of social influence for this contagion. This challenge has evoked an embarrassment of riches, for there are several, though complementary, explanations. An important argument is that these changes are due to broad cultural shifts. In this view, the changes in social norms are part of what may be called the growing ‘financialization of corporate culture through the diffusion of such practices as pay for performance (Krippner, 2011), a view recently echoed by some economists (c.f. Levy and Temin, 2007; Frydman and Saks, 2010). While such broad shifts are revealed through macro-observations on the growing weight of finance in many developed economies, the question which we address is what micro-processes generate these changes, at least in the context of executive pay.

Three explanations point specifically to the diffusion of high pay as a process of contagion in a network. The first is suggested by the pay for performance literature that points to the role of corporate board networks in facilitating contagion. Davis and Greve (1997) and Davis, Yoo, and Baker (2003) find that managerial practices such as poison pills and golden parachutes spread through board networks; similarly, Sanders and Tuschke (2007) found that board interlocks had a significant impact on whether German firms adopted stock option pay in Germany. Similarly, recent work in financial economics and accounting have shown a relationship between board networks and executive pay (Barnea and Guedj, 2006). A second process is social comparison through the use of benchmarking to peers and the possible ratcheting effects noted by DiPrete, Einich, and Pittinsky (2010). The third explanation emphasizes educational affiliation networks, whereby graduates from the same undergraduate colleges or higher education programs, such as MBA schools, share and compare salary information (Hwang and Kim, 2009; Engelberg, Gao, and Parsons, 2009).

Our methodological approach is to focus on a central question: what mechanism explains the rise in executive pay? We utilize the bench line economic model that links pay to size to predict pay levels by market value to generate our key variable of interest (as in Gabaix and Landier, 2008). The residuals off this bench line provide a first-order measure of under- and over-pay of executives for a given year; this measure is similar to the methodology found in Wade, O’Reilly, and Pollock (2006). This measure then permits an application of a contagion model to identify the mechanism by which high pay diffuses, leading to pay levels for executives colloquially labeled ‘fat cats. Using
a Generalized Estimating Equations (GEE) model and dyadic logit specification (departing from the method of Christakis and Fowler, 2007), our initial estimates suggests that all three network influences of board interlocks, peer groups, and educational affiliations matter.

Young (2009) has recently raised the specter of model uncertainty as plaguing causal identification in empirical research. This concern is well placed in the context of this study. Contagion via a network is likely to be mistaken for a common latent variable, for, after all, social networks condition the behavior and yet themselves are generated by unobserved social motivations, such as similarity or homophily. If similar firms tend to be linked by boards for unobserved reasons, the effect of board interlocks on pay may be due to this unobserved similarity that also leads to similar pay levels; the network effect on pay is spurious. It is therefore important to check for spurious causality by endogenous mechanisms. We devise two mechanisms to explore spurious causality to address these concerns. The results points to the importance of peer comparisons as a principal factor on pay, supporting the contagion mechanism emphasized by Diprete, Eirich, and Pittinsky.

2 Theory

Ambiguity lies at the core of the determination of price and value economic markets. How much is something worth is a question that frustrates many a tourist unaccustomed to bargaining in the bazaar markets found in most countries. But it is also critical to the question of how much am I worth? Very often the solution to such questions is to compare prices for similar goods, but similarity is itself often an elusive definition. The determination of worth is deeply troubled by fundamental ambiguity and multiple logics of evaluation (Stark, 2011).

Economics, as traditionally defined, does not resolve these issues. The fundamental dilemma posed by markets is the ambiguity regarding price and value, and their relation with each other. The Walrasian neo-classical economic approach was to regard prices arising out of an auction where demand and supply would clear. This fictional device is theoretically useful, but does not resolve the fundamental problem. Not only are relatively few goods and services sold by auction, the dynamics of auctions do not assure that prices converge to value, giving way to such sentiments as buyer’s remorse, the winner’s curse, and endowment effects. Even fairly homogeneous goods, such as shares in a company traded in financial markets, are subject to vastly varying assessments of value, leading to a large literature on the question do stock prices reflect fundamental values. In other words, ambiguity is an essential aspect of markets.
From the perspective of the employer, one solution is to rely on rules as conventions (Favereau and Lazega, 2002). In the aggregate, a firm cannot pay more than it earns, but except for single proprietorships, this constraint still leaves considerable variation. For financial firms, a common rule is to pay out 50% of it revenues in compensation (Elliott, 2010). This rule has two effects: there will be a lot of heterogeneity between firms, since some firms earn more than others, and there will still be the potential for a lot of variance within a firm. As it is indexed to top-line revenue, this policy is correlated with, but distinct from, the market value and pay relation suggested by Gabaix and Landier.

Another solution, which is embedded in the principal-agent models, is to pay people for their marginal revenue contributions. It’s hard to assess how often this rule is used for managerial work and in many contexts, such as law firms where the direct margin contribution to revenue is known through billable hours, pay is often set also in deference to other norms, such as seniority, fairness, and broader contributions. In most cases, the marginal contribution is completely unknown. Thus, pay must be indexed to a noisy and correlated signal.

Since it has so dominated the academic discussion of pay, it is useful to consider further the principal-agent model as a way of motivating the contribution of a sociology of managerial pay. The standard principal-agent model recognizes that effort is not observable, and thus firms use incentive schemes to motivate workers. For the kind of work that executives do, the measurement of effort is difficult to ascertain and incentives are invariably attached to signals, such as stock prices, that are noisy or imperfectly correlated with “true” performance. The problem remains then of figuring out how much incentive pay needs to be promised to get someone to do something.

Leaving aside the many technical issues, the principal-agent model begins with the data that individuals know their reservation wage or salary. This is an example of ‘egocentric’ ambiguity highlighted in Podolny (2001). It could be expected that such ambiguity would be lowest for valuing what to pay

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6 See Bolton and Dewatripont (2005) for a discussion of the technical challenges. Balachandran, Kogut, and Harnal (2011) analyze econometrically the inconsistency between the standard model and the risk behavior of CEOs of banks through the financial crisis. There are many technical reasons to be wary of principal-agent models of imperfect contracting applied to CEO pay. The most interesting is the standard assumption of constant absolute risk aversion preferences, which states that $10 of extra income has the same utility for an individual, no matter if she is driving a taxi making $40,000 a year or running a hedge fund making $10 million. If constant relative risk aversion is assumed, the model is invariably hard to close, but as important, the implications for how much money that has to be paid to motivate someone who is already wealthy to do something are unreasonable.
people, for individuals should be informed as to their own value. Surely, the job of a CEO is complex and it is hard to know fully before taking it what it will be and how well it will be accomplished. Introspectively, you can run the experiment and ask whether you would take the job of running a large public firm for a million dollars? What about $1.25 million? The .25 million ($250,000) alone puts you near the top 3% of income earners. In other words, our assessment of our reservation wage does not spring forth epiphenomenally, so that we ‘know’ it has to be $1 million.

One influence will be what might be called ‘habit formation’, what is the wage that one is used to earning? Considerable evidence speaks as well to an endowment effect, something is highly praised once it is owned. People also form habits regarding their expected life styles, what they are used to earning, what they feel their past record has proven. We will later statistically exploit this habit formation in our estimations. On the side of the employer, the principal-agent model relies upon an important theorem that states incentives should be based only on signals that are correlated with true performance (Holmstrom, 1979). For example, if the price of oil moves by exogenous events unrelated to CEO ability, then this randomness should be filtered from the profit, or stock price, signal to which the CEO’s pay incentive is likely to be tied. Rather, pay incentives should be indexed to signals of relative performance. Yet, in practice, this filtering of common trends from the pay package is generally ignored.\footnote{Bertrand and Mullainathan (2001) find that contrary to theory, pay to oil company CEOs moves with the price of oil, though the effect is dampened for those companies with better governance practices. They find evidence that better governed firms are more likely to filter out some of the exogenous noise.}

Given the difficulty of the measurement of productivity, a natural solution is to ‘look around’ through social comparisons outside the firm with relevant alters—this comparison poses a problem of ‘altercentric’ ambiguity. That actors infer their abilities through social comparison has long been recognized in the social psychology and literatures, and those who are proximate in both a spatial and demographic sense are particularly highly salient as a referent group for gauging one’s abilities (McPherson, Smith-Lovin, and Cook, 2001; Festinger, 1954). Frank (1985) argues that people sort themselves into local hierarchies as a basis for status competitions, and this in turn determines the rewards that are deemed to be equitable. According to Frank (1985), local status is particularly important for those at the high end of the wage distribution, suggesting that social comparisons between similar peers may be pronounced for CEOs.\footnote{O’Reilly III, Main, and Crystal (1988) initiated this line of research for executive pay, finding a relationship between the pay of the compensation committee and the CEO.} It is not realistic that the CEO candidate will know fully the opportunity costs posed by the market, but she can form guesses based upon
comparisons with others. On this point, economics and sociology agree; the disagreement is over the process by which the comparison group is chosen. As studies show on the determination of pay for employees in general, wages inside of firms are set according to job classification and social comparisons. (See the classic study Doeringer and Piore, 1971.) The utility of classifications is that they determine the set of people for comparison. People tend to form their sense of their reservation wage, below which they would not work, in terms of what seems to be the ‘practice’, what is the on-going ‘wage’, what is the ‘fair’ wage, what is the wage of my ‘aspiration’ group.

The altercentric considerations are data that are open to the party that gives the wage. Those whose responsibilities are to bargain the salary of the CEO may be interested in fairness but, surely, the acquisition and retention of the CEO are central concerns. For the public firm, the board of directors is responsible for determining the salary contract for the CEO. How do they form estimates of fair worth? There are three obvious sources discussed in the literature.

The first are board networks. The studies on the adoption of a specific policy of pay for performance show evidence for the spreading of these pay practices through board interlocks, as first noted by O’Reilly III, Main, and Crystal (1988). Pay for performance policies increase the riskiness of pay for executives. A principal agent model proposes that CEOs must be compensated for this risk, increasing pay levels. However, the adoption of formal pay for performance policies begins in the 1980s after pay levels had already started to rise, though pay levels remained elevated after the dot.com bubble burst in 2001 (Frydman and Saks, 2010). Still, regardless of the exact effect of pay for performance adoption on pay, the spreading of pay through director networks represents one candidate explanation for the diffusion of higher pay.

Since a director can sit on more than one board, she has information about the salaries and salary procedures by which comparisons can be made. The published literature reports positive effects for the social influence revealed in the remuneration of CEOs linked to each other through their board interlocks. Barnea and Guedj (2006) for example find that pay increases in the degree of the board; a CEO of a firm which is in the top quintile of connected firms receives a 10% higher salary and a 13% higher total compensation than a CEO at the bottom quintile of connected firms. Larcker, Richardson, Seary, and Tuna (2005) find that pay increases with shorter path lengths between inside and outside directors, and CEOs and compensation committee directors. Liu (2010) found that ties between boards had a stronger positive effect than ties among CEOs on the diffusion of pay.

There is though an important challenge to these results. Since board interlock networks are non-directional, pay increases should be reciprocal. This reci-
proximity makes it difficult to identify causality. For example, since high status boards are linked, high pay levels and increases may be reciprocated. However, this apparent reciprocity may be due to sensitivity to latent factors, such as a general increase in the demand for CEOs who know how to run complex organizations. The identification problem ensues from figuring out if the correlation across high status boards is due to contagion or to having similar CEOs. It is a common property in social networks that similarity breeds ties through homophilous matching, whereby all ‘like’ high status boards will share directors and will tend to hire high status CEOs. If changes in the demand for CEOs vary by their status (which may be related to their inherent abilities), the social influence effects will suggest spurious contagion when instead they are due to a correlation with the latent demand for their services. Manski (1993) calls this the reflection problem. Below, we design a comparison model to identify the effects should the network tie be broken.

The second way that salaries may be determined by boards is through benchmarking to peers. Benchmarking is the mechanism for White’s theory on the origins of markets, for by this process, salaries are not established by generic supply and demand conditions, but in reference to other producers (White, 1981; see also Favereau and Lazega, 2002). In the case of CEO salary determination, these other producers are the firms in the set which CEOs, directors, and/or consultants view as similar.

There is a fairly substantial literature on the effects of peer comparisons on pay. Wade, Porac, and Pollock (1997) were among the first to find evidence for the public acknowledgment of consultants for setting the highly-paid CEOs. Bizjak, Lemmon, and Naveen (2008) find that peer comparisons (which they select by matching to similar size and same industry firms) leads to larger pay increases for low pay CEOs and to higher turnover; they interpret their results as consistent with the primacy of the market in determining pay. In an article whose methodology we use to construct peer groups, Faulkender and Yang (2010) find that firms appear to select highly paid peers to justify their CEO compensation and this effect is stronger in firms where the compensation peer group is smaller and the quality of governance appears weak. It is noteworthy that these two latter papers reach opposite conclusions as to the merits of peer benchmarking—the first inferring market efficiency and the latter poor governance, but both suggest the practice leads to the diffusion of higher pay.

DiPrete, Eirich, and Pittinsky (2010) propose a theory for escalating CEO pay that relies upon this peer benchmarking mechanism. Benchmarking differs from board networks in the important respect of generating what they call cognitive networks; unlike board interlocks, these networks are directed, since a firm that considers another firm a peer may not be in the latter’s peer group. The surveys on peer benchmarking indicate that firms frequently rely on peer comparisons with firms in higher compensation deciles. Clearly, this policy
leads to a ratcheting of salaries that percolates through all companies. This bias in the benchmark selection is consequential due to feedback effects. As they explain,

“small and shifting fraction of CEOs have regularly been able to “leapfrog” their compensation benchmarks by moving to the right tail of the benchmark distribution and get larger than normative compensation increases, even after taking job mobility and executive performance into account. These events produce subsequent “legitimate” pay increases for others, and potentially explain an important fraction of the overall upward movement of executive compensation over the past 15 years. (1673)”.

The endogeneity issues involved in peer benchmarking is different than those for board networks. By construction, peer CEOs are chosen on the basis of similarity to the focal CEO. Correlation is in fact not spatial in the sense of the board network graph, but intrinsic—the cognitive work is generated by the search for relevant social comparisons. In this case, homophily and pay determination appear linked by construction. However, this correlation is consistent with the theoretical argument, since peer networks are ‘selected’ by a focal firm to identify ‘like’ CEOs for the purpose of comparison. We will, in fact, select the peers borrowing a calibrated propensity score estimated on observed peer selection. Thus, an appropriate baseline comparison is to compare the effect of benchmarking against what a random assignment would produce.

In addition to these two arguments, a third social influence on the setting of pay is educational. Defining social ties to include education as well as other shared affiliations (e.g. military), Hwang and Kim (2009) found that holding a diploma from the same institution within a three year window increases pay. Engelberg, Gao, and Parsons (2009) find that an additional connection to an executive or director outside the firm increases a CEO’s compensation by almost $18,000 (.07%) on average and explains about 10% of total pay. This is a strong statement on the causal effects of network ties and is subject to the above concerns over endogeneity discussed above. However, they also find a strong effect of the number of school connections, after controlling for school fixed effects.

The endogeneity concerns for the educational network are less troubling than in the case of social networks. School connections are formed during youth and prior to managerial careers, and consequently, reverse causality due to the acquisition of connections because a CEO is prominent and well-paid is ruled out. However, much like the problem in the principal-agent literature where ability and effort cannot be observed, educational ties is confounded by human capital considerations. We control for human capital effects by including a variable for graduate education. Still, we are not sure if this confound is
entirely purged if one believes that universities vary in quality and high quality students go to the better ones. In absence of a natural experiment (such that some students are randomly assigned to universities) or observations on quality (such as SAT scores), this possibility cannot be entirely eliminated. We utilize again a bench line of randomizing assignments to generate estimates for a random model and against which we can compare the estimates. We also vary the cohort window of comparison to show narrower windows produces better results; this result is not easily reconciled with a concern that the educational effect is driven by an unobserved quality not captured in our human capital variable.

2.1 Summary

The ambiguity over value is not resolved by an appeal to market efficiency, since the functional relationship between CEO ability and effort to performance is noisy and subject to social comparisons and influences. DiPrete, Eirich, and Pittinsky (2010) note that a social comparison has, minimally, the implication of contagion and, secondly, if biased towards higher wage earners, for escalation. Bizjak, Lemmon, and Naveen (2008) and Faulkender and Yang (2010) studies implied similar dynamics of contagion and escalation.

The above discussion suggests a straightforward empirical strategy. The first is take a naive approach to the standard economic model and assume that CEO pay is determined proportionally by firm size, as measured by market value. Market value is an appropriate measure, as its value is higher if the leveraged return on assets is higher; thus ROA is embedded. Since leverage also affects risk and risk influences pay through option pricing, we also control for stock volatility in the estimated model described below. This estimated relationship of pay and firm value generates predicted pay, from which we then calculate the residual following the methodology of Wade, O’Reilly, and Pollock (2006). High pay is coded as 1 if the residual is positive, and zero if not. Since the binary variable of high pay is dynamic, we treat it as a state that varies over time.

We proposed above that expectations regarding pay respond to egocentric and altercentric influences. Egocentric refers to expectations of self-worth, which suggests a habit-formation dynamic in which past pay predicts subsequent pay. Even if a positive residual in one year is due to random error, it will have an effect on next year pay through influencing expectations. We thus lag the state of high pay by one year, similar to the approach in dynamic panel analysis. We expect the lagged variable to be positively related, though over time, there will be mean reversion. The altercentric influences pay through social comparisons. These comparisons will be through sharing common board
members, benchmarking against peers, and educational networks. As indicated above, board network affiliations are especially subject to endogeneity problems, where common attributes may determine both pay and network ties through assortative matching on prestige and quality. However, peer and educational affiliations may also be due to unobserved quality and attributes. We thus devise a statistical strategy by which to strengthen the causal inferences, as discussed below.

We turn now to discussing the data, variables, and model specification.

3 Data and variable construction

The data for this study come from a number of different sources. Compensation figures of CEOs come from the Compustat ExecuComp database, which provides compensation data for the top five executives of over 3,000 firms since 1992. Board of director memberships were derived from the Riskmetrics database, while broader firm-level data on market capitalization, sales, industry SIC code, etc. were obtained from COMPUSTAT annual files. The BoardEx database provided detailed demographic information on CEOs such as gender, age, and educational affiliation.

Figure 1 shows the trend of total compensation of CEOs in our dataset from 1992 to 2009, and how the different components of pay (i.e., salary, bonus, options, etc.) have changed over time. Compensation rose sharply in the late 1990s, coinciding with the technology boom, fell during the bust, and maintained a steady level up to the financial crisis of 2008. A noteworthy trend in the components of pay is the dramatic rise and fall of options as a form of compensation. At its peak in 2000, options accounted for more than 66.5% of the average CEO’s compensation, which contrasts with the 30.3% eight years before, and 22.5% nine years after. Such swings in the composition of pay suggest that the norms governing CEO pay are quite sensitive to the social context.

Figure 2 charts the distribution of board of director ties over time; the number of ties per director is also called the ‘degree’. The important observation to make is the steeper fall-off in degree for the year 2008 compared to earlier years. This decline reflects potentially the influence of the Sarbanes-Oxley Act passed in 2002 that increased the responsibilities, and liabilities, of directors to the board. This decline, along with a shortening average path length among directors, has also been found in Chu and Davis (2011).
3.1 Dependent variable

As explained above, we utilize the equilibrium models of CEO pay of Gabaix and Landier (2008) to establish the market compensation level based on firm size. We retrieve the total compensation (salary, bonus, restricted stock granted, and Black-Scholes value of stock options granted) of all CEOs from the ExecuComp data set covering the period of 1996 to 2008, and regress the logged value of these observations over the log of total market capitalization for each firm in the preceding year.

\[
\log Y_i(t) = \alpha + \beta \log MC_i(t-1) + \epsilon_i,
\]

where \( Y_i(t) \) and \( MC_i(t) \) is the total compensation and the market capital of board \( i \) at year \( t \), respectively. We do not include any industry or year fixed years, although the residuals clearly trend over time; by 2008, over 70% of the state variable is 1. Our thinking relies upon the analogy with obesity, which is measured independent of time. Later, in the GEE specifications, we allow for time fixed effects, whereas industry effects are absorbed in the lagged state variable.

Taking this equation as a baseline for what a CEO’s compensation should be if pay was determined by a pure market process, we then treat the residuals as a phenomenon of interest to be explained. Using the coefficients obtained from the OLS regression, we calculate the residual of each year-CEO observation \( (R) \) by subtracting the actual total compensation \( (Y) \) from the predicted compensation level \( (\hat{Y}) \) based on the total market capitalization at \( t - 1 \). Each CEO in our sample is thus, one of two states in a given year:

\[
S = \begin{cases} 
1 & \text{if } R > 0 \\
0 & \text{otherwise}, 
\end{cases}
\]

where \( S \) is the state.

In Figure 3a, we plot these residuals around the predicted line. The residuals are normally distributed, as can be seen by the spherical cloud centered on the diameter of the predicted (log) linear relationship. Figure 3b highlights the values for financial service firms, since there is a common belief that these executives are relatively higher, if not over, paid than those in other industries. Clearly, the relatively high pay for financial firm executives is related to the high market values of finance companies. Market values may of course represent ‘economic rents’ that vary by industry, and thus the relationship represents a proportional sharing of value, however earned.
3.2 Social Influence Variables

The director network is built from the bipartite graph that links CEOs and boards. Of the 4,641 CEOs in our sample, 40.1% are isolates with no board links to other CEOs; overall, the mean degree is 3.16, with a maximum of 34. For the year 2008, the proportion of isolates is 36.8%; the giant cluster contains 34.1% of the CEOs, with a diameter of 13. Thus, the director network is fairly fragmented, with a larger core of directors who are well-connected. We build a CEO to CEO non-directional network by taking the projection of the bipartite graph, thus linking each CEO to its CEO alters, that is the CEOs who are in his or her neighborhood. As explained more fully below, we treat each link between a CEO and CEO alter as a dyad.

Because of regulatory and competitive factors, the overall network topology of director varies by industry, as illustrated in Figure 4 that shows the board ties for the electronics industry and financial service industries. Board ties are not permitted by regulatory law for banks, whereas telecommunications companies share many directors. If shared directors matter to contagion, then these regulatory influences should matter to the diffusion of high pay.

The second influence is peer comparisons. In 2006, the Securities and Exchange Commission (SEC) issued a new regulation that mandated firms to disclose whether they engaged in any benchmarking of total compensation, and the companies that comprise the benchmarking group. As the rule came into effect for fiscal years ending in December of 2006, it is not possible to identify the companies a focal firm used as peer for benchmarking purposes in previous years. In their study, Hwang and Kim (2009) chose peers based on similar industry and size; DiPrete, Eirich, and Pittinsky (2010) imputed peer groups based on industry, size, performance, and aspiration (i.e., firms larger than the focal firms).

Since Faulkender and Yang (2010) analyzed the disclosed peer groups as of 2006, they were able to estimate the parameters to model predicting the choice of the actual peer group disclosures from fiscal years ending in December 2006 to November 2007. They estimated the likelihood that firm $j$ would be part of firm $i$’s compensation peer group based on indicators of industry, sales, and inclusion in various stock indices. They thus provided a propensity score estimation for peer group choice.

We exploited their results to identify peer CEO alters by taking the estimated coefficients from their regression analysis, and calculating the propensity score.
for each of the possible firm pairs, using the following equation:

\[
\text{Propensity Score} = 1.156 \times \text{Match(two-digit industry)} + 0.813 \times \text{Match(three-digit industry)} + 0.414 \times \text{Dummy(Sales within 50–200\%)} + 0.293 \times \text{Dummy(Assets within 50–200\%)} + 0.119 \times \text{Dummy(Market cap within 50–200\%)} + 1.744 \times \text{Match(Dow30)} + 0.444 \times \text{Match(S&P500)} + 0.048 \times \text{Match(S&PMidCap400)} + 0.114 \times \text{Match(CEO is chair)} - 0.052 \times \text{Match(CEO is not chair)} + 1.137 \times \text{Dummy(Talent flows)} + 0.011 \times \text{Number of peers} - 3.236,
\]

where \(\text{Number of peers} = 18.25\).

Matches in industry were determined based on two and three digit SIC codes, sales, assets and market capitalization comparisons were based on data from Compustat. The propensity score calculation also takes into account whether both the potential peer and the firm are or not the chairmen of the board of directors, and whether any of the top executives moved between the firm and its potential peer during the time period from 1992 to year \(n\). As we do not have the actual number of peers for firms, we include the median number of peers as 18.25 identified by Faulkender and Yang (2010).

The propensity scores that were calculated from this equation for the 9 million potential peer relationships ranged from -3.08 to 3.19, with a mean value of -2.62. We assigned firm \(j\) to firm \(i\)’s peer group if the propensity score was above 0, as this criterion yielded the closest mean number of peer firms for the imputed peer groups to the mean number of peers (i.e., 18.25) observed by Faulkender and Yang (2010). Per the discussion below, we also changed the band of 50\% to 200\% to check for sensitivity and also to bias the ‘aspiration’ peer group upward to test for the ‘leapfrog’ effect.

The final social influence we examined is the educational network defined by graduation from similar schools. As mentioned above, we collect the educational affiliations of all CEOs from the BoardEx database. Since individual or company IDs in BoardEx cannot be linked to the ExecuComp database, we created a name-matching algorithm that is a variation on the Levenshtein algorithm, which computes the least number of operations necessary to match
We first match BoardEx’s board ID (i.e. firm identifier) to Compustat’s GVKEY identifier to create a link between firms in the two databases. We then match individual IDs using the same algorithm, but as the format of BoardEx’s naming format (e.g., A. Einstein) differed from ExecuComp’s (e.g., Albert Einstein) and resulted in ambiguous matches, we took all potential candidates and selected the matching individual based on a criteria of whether the company IDs for the CEOs matched each other. This procedure resulted in 12,103 matches out of 36,554 CEOs.

With CEOs matched from the BoardEx database, each CEO was assigned to an undergraduate alma mater as well as to a graduate school if applicable. An alter CEO is thus someone who graduated from the same educational institution; we report results using no window and a 10 year window around graduation times of ego and alter CEOs to identify the dyadic matches.

The numerical frequency of CEOs per educational institution is given in Table 1. As can be seen, Harvard has a remarkably high number of graduates who became CEOs of the largest public corporations in the US; the total number of CEOs who graduated from Harvard is 343 out of a total number of 2,018. This frequency is also consistent with the Cohen and Malloy (2010) study that found that 9.3% of Senators have under-graduate or graduate degrees from Harvard; 6 of the 9 current Supreme Court Justices are graduates from Harvard Law School. The total proportion of CEOs exceeds 100% as individuals are often part of multiple education networks (i.e., undergraduate and professional).

### 3.3 Control Variables

We included a number of control variables that are thought to have an influence over the propensity to be over or underpaid. First, we include the gender of the CEO, as prior studies have found that a significant gap in compensation exists between men and female executives (Bertrand and Hallock, 2001). We also include a control for the tenure of the CEO in the current company (Hill and Phan, 1991), and volatility of the stock, as standard in the CEO compensation literature (Core, Guay, and Larcker, 2003). Changes in the top executive position can also have a significant impact on compensation, so we include a dummy variable noting whether the CEO is new to the position in that given year, and another dummy variable indicating whether the CEO was

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9. We thank Jordi Colomer for providing the code for the name matching algorithm.

10. Graduates from short-term executive education programs were excluded as part of the education network, when this was clearly marked in the dataset. Additional analyses including CEOs with Executive Program or Advanced Management Program (AMP) as degree type yielded similar results.
promoted from the inside of the corporation, or brought in from the outside. The mobility effect on compensation plays an important dampening role on the possible tendency of the model to predict an exploding cascade of over pay, and will be used at the end to show the stability properties of the estimates through a simulation model.

3.4 Descriptive Variables

Table 2 and 3 report the descriptive statistics and correlations between variables. The average CEO in our sample is 55 years old with 8 years of tenure in their current position, and receives a total compensation of $4.6 million. Consistent with other studies, a very small number (2%) of women join the chief executive ranks. Fifty-three percent of the CEO-year observations are classified as “overpaid” according to our definition, and the average residual off the regression of logged compensation on logged market value is 0.02. This residual is called interchangeably “high pay” or “overpaid” when positive; “low pay” or “underpaid” when negative. Over- or underpaid are in reference to the basic market relationship we estimate and are not used as a value judgment on the compensation decision.

As expected, compensation is positively correlated with firm performance metrics such as profitability and sales, and these measures are in turn highly correlated with market value, suggesting that market value adequately captures size and other demands of management skills. The lack of correlation between overpaid state and market value imply that our empirical approach of residualization reasonably incorporates managerial complexity and talent as a baseline explanation, allowing us to examine the social sources of variance in pay.

4 Model Specification

The main model for our analysis is a longitudinal logistic regression model. This model treats each ego and alter pair as a dyad. For example, in the well-known study on the diffusion of obesity by Christakis and Fowler, the binary state variable is determined by a critical value of body mass and the independent variables are ego’s previous body mass state and the previous state of alter—this is the network or peer effect; in addition, they controlled for a vector of characteristics. In our case, the binary state variable of the focal (i.e. ego) CEO’s high paid status in a given year $(t)$ is a function of the CEO’s high paid status in the previous year $(t-1)$; and most importantly, the high paid status of CEO alters who can potentially exert social influence on
the focal CEO in the same year \((t)\). Since this specification involves multiple observations across years, and CEO pairs for each CEO, there is substantial violation of the standard moment conditions.

We utilize therefore a generalized estimating equations (GEE) model to estimate the following model:

\[
\text{logit}(p) = \beta_0 + \beta_1 S_{ego}(t-1) + \beta_2 S_{alter}(t)
\]

\[
+ \beta_3 V_{ego}(t) + \beta_4 G_{ego} + \beta_5 T_{ego}(t)
\]

\[
+ \beta_6 N_{ego}(t) + \beta_7 O_{ego}(t) + \beta_8 HC_{ego},
\]

where \(S(t)\) is the overpaid state of CEO at time \(t\), \(V(t)\) is the volatility of stock, \(G\) is the gender of CEO, \(T(t)\) is the tenure, and \(N(t), O(t),\) and \(HC\) are dummy variables for new CEO, outsider CEO, and human capital, respectively.

We calculate the increase in likelihood of ego overpay based on the odds ratio \(R\), which is defined as

\[
\log R = \text{logit}(p_1) - \text{logit}(p_2),
\]

to see the effect of alter’s overpaid status on ego overpay, \(p_1\) is set as \(S_{alter} = 1\) and \(p_2\) as \(S_{alter} = 0\), and thus, \(R = e^{\beta_2}\). The GEE model produces ”population averaged” measures which is specific to the clusters (i.e. networks) in the sample; the odds ratio is then a comparison of the probability \(p_1\) of the individual randomly chosen from the population to the probability \(p_2\) of an individual also randomly chosen from the population.

The inclusion of the lagged ego dependent variable allows us to investigate change in the status of the focal actor, while also controlling for many unobservable characteristics of the CEO and firm. The alter state is contemporaneous with that of ego, since the social process behind pay determination involves social comparisons made at the time. While we believe that the influence of alters is best captured within the same period, we have also conducted the analyses with a lagged alter state variable to address concerns of simultaneous causation (Lyons, 2011) with similar, though slightly weaker, results. We presume that the more salient social comparisons are for the current year, and we thus report these results. We are sensitive to the Shalizi and Thomas concern over the implied stability of the system showing simultaneous feedback (Shalizi and Thomas, 2011). We perform a simulation using the estimated values to check for the dynamic stability.

The GEE model provides a general covariance structure to account for potential correlation between observations (Liang and Zeger, 1986). We assumed an independent correlation structure based on QIC fit statistics.
The Christakis and Fowler GEE dyadic model does not resolve completely the identification issues. They sought to identify the network effect by showing that a significantly higher increase of an individual’s body mass index was caused by the obesity of someone that the individual named as a friend as opposed to someone who had named the individual as a friend. By showing that the directionality in the network correlated with causal direction, they inferred causality. If unobserved common effects were responsible for the correlation, then direction of friendship should not matter; the directed friendship would matter if an ego learns from an alter named as a friend, but the alter does not name the ego as a friend. Christakis and Fowler conclude that obesity is governed by the same epidemiology as a disease that spreads in a social network.

Still, this directionality does not fully respond to the potential influence of common unobserved effects due to homophily. Matching individuals through propensity scoring and using detailed dynamic data on personal and social characteristics, Aral, Muchnik, and Sundararajan (2009) find that peer influence in product adoption decisions in this network are overestimated by 300-700%, and that homophily explains over half of the perceived behavioral contagion. However, the effect of unobserved homophily that is not captured in the propensity model may still lead to further confounded causality. In an otherwise pessimistic assessment of the hope for causal identification in the context of social networks, Shalizi and Thomas (2011) make the proposal that access to a counterfactual could suffice for identification. They note that

“...the presence or absence of a social tie \( A_{ij} \) between individuals \( i \) and \( j \) provides information on the latent variable \( X_i \), whether we implicitly include the tie by predicting \( Y_i(t) \) from the past values of neighbors \( Y_j(t-1) \) or we explicitly add \( A_{ij} \) to the prediction model. In the language of graphical models, conditioning or selecting on \( A_{ij} \) “activates the collider” at that variable. This suggests that we would do better, in some circumstances, to construct a useful inference by deliberately not conditioning on the social network, thereby keeping the collider quiescent’ (Shalizi and Thomas, 2011: 228).”

To rule out endogeneity as a driver of the results observed in the director network models, we leveraged the longitudinal nature of our data to construct “latent” networks consisting of ties that have yet to have been realized, but will form at some point in the future. For example, if Firm A and Firm B establish a new tie through a common director starting from 2002, we focus on the pre-2002 period and examine the extent to which Firm A’s overpaid state has an effect on Firm B’s transition to overpay. If compensation practices are diffusing through networks, then one should not expect to see any effect of Firm A on Firm B due to the fact that they are not connected yet. On the other hand, if A and B are similar in their state because they are similar
in ways that later drive them to share a board of director member, then one should observer a positive influence of \( A \) on \( B \) (or vice versa) even though no ties bridge the two together.

Finally, to rule out the possibility that our findings are a statistical artifact of the model specification, we construct randomized networks for each type of alter to serve as a baseline network effect. For each type of network, we keep the ego’s degree identical to the observed network, but randomly shuffle the alters from other egos who are part of the observed network in that given year. For example, if in 1996 our sample had CEO \( A \) connected with CEO \( B \) and \( C \) via common board of directors, while \( D \) is connected to \( E \) and \( F \) to \( G \), one possible outcome of shuffling is \( A - E, A - G, D - B, \) and \( F - C \). By switching among CEOs that are already part of the network, alters in the randomized networks will still possess any unobserved characteristics that make them likely to be a board interlock, peer, or alumni. Furthermore, if broader social norms about pay that influence all firms are driving the simultaneous change to overpaid status, then the randomized networks should help us capture and establish these context effects as a baseline.

5 Empirical Results

Our models estimate the likelihood that a focal CEO (i.e., ego) transitions from an underpaid state \((S = 0)\) to an overpaid state \((S = 1)\). We hypothesized how different categories of alters—those based on ego’s board of director network, those who are in the cognitive peer group network, and those based on educational affiliations—will influence this transition, and used GEE models to test whether an alter being overpaid leads to ego becoming overpaid in a given year.

First, Table 4 shows the results for the influence of alters resulting from board of director interlocks. Based on the first panel of results (Model 1 through 5), the results point to high pay diffusing through director networks. Either CEOs observe the increase in the network neighbor’s pay and demand a similar increase from the common director, or the common board member uses the standard he/she applied in setting the pay for one CEO in determining the value of the other CEO to the firm, the result suggests that network ties that bind CEOs together have a causal effect on the likelihood that CEOs will be overpaid.

The effect of the lagged state of the CEO on the current overpay state is strong and significant in all models, with CEOs overpaid (underpaid) at \( t - 1 \) being five times more likely to be overpaid (underpaid) at time \( t \) \((p < .01)\). This strongly suggests that pay states are somewhat stable across individuals over
time.

Other control variables show a significant relationship with overpaid status as expected. New CEOs are less likely to be overpaid if they are promoted from within the firm \((p < .01)\), while outsiders are more likely to receive compensation that exceeds the amount suggested by the firm’s market value, consistent with prior work presumed overbidding for outside corporate “saviors” (Khurana, 2002). CEOs also had a higher likelihood of being overpaid if they possessed an MBA or PhD degree, suggesting that educational signals are important for even the uppermost parts of the labor market.

The gender of the CEO did not have a statistically significant effect on the CEO’s overpaid status, and CEO tenure does not show any statistically significant relationship with overpay once the models account for a CEO’s newcomer and insider/outsider status. The non-negative coefficient for gender indirectly supports prior arguments that posit that the significant gap between genders in executive compensation is mainly driven by differences in firm size under management (Bertrand and Hallock, 2001). In addition, volatility of the stock was highly correlated with overpaid status, but the effect was not statistically significant.

While these results seem to point to a strong contagion effect via board of director networks, on closer inspection, these results alone cannot rule out a key alternative explanation common to much network research: endogeneity. Rather than network ties acting as a channel through which information and influence flows, it could be that firms that share directors are similar in unobserved ways that also happen to make them transition to an overpaid state at similar periods of time.

Using the latent network design described above, we looked at the transition to overpaid status for firms before they form ties. To recall, the idea of a latent network is to use our knowledge that two CEOs will be linked by a network director tie to create a ‘latent tie’ prior to that formation. Thus, we can isolate the homophily effect and estimate the model; the alter effect is now capturing homophily rather than a network influence.

Models 6 through 10 replicate the columns of the director networks, but instead of setting director ties as the “alter”, we replace CEOs who will eventually become a tie for a given CEO as the alter. As seen in Models 8, 9, and 10, the coefficient for “Alter Currently Overpaid” is positive and statistically significant \((p < .01)\). Furthermore, the coefficient is not statistically distinguishable from the observed director network effects, implying that the ties are simply a reflection of an underlying propensity for certain CEOs to be overpaid, rather than a causal driver of contagion.
5.1 Peer Groups

We then estimated the likelihood that firm $i$’s CEO would transition from an underpaid to overpaid state in relation to the transition of a projected peer’s CEO transition. We focus on the egocentric and altercentric estimates, since the estimations of the other variables remain largely the same. The results shown in Table 5 confirm prior work on benchmarking (DiPrete, Eirich, and Pittinsky, 2010) that suggest social comparisons among peer group members leading to ratcheting effects in pay. The transition of a peer to an overpaid state increases the odds that a focal firm’s CEO will become overpaid by over 30%.

Furthermore, the effect of social comparison varies depending on the extent to which alters are similar to the ego. The propensity scores calculated for peers effectively provides a measure for the similarity between ego and potential alter along a number of characteristics that are salient to CEOs and board of directors. By varying the criteria for inclusion as a peer, we were able to construct groups of alter CEOs that ranged from the most similar, to those who differed on all dimensions. The results shown in Table 5 were based on selecting firms that had the highest score in our propensity score calculations. When constructing the peer groups by selecting firms that are the 99th percentile of propensity scores, the GEE estimate of the coefficient for alter overpaid state was 0.205, which is significantly lower than the 0.299 estimate for the most similar firms ($p < .05$).\footnote{Full GEE Estimates are available from the authors upon request.} For firms scoring in the 90th percentile, the coefficient for alter state was 0.05, still positive and significant ($p < .05$), but considerably lower than the original estimate, while those in the 75th percentile had a coefficient of 0.015, indicating no statistically significant effect on the overpaid state of the ego CEO. Interestingly, when choosing the most dissimilar firms from the focal firm based on the the lowest propensity scores (i.e., 0 percentile), the coefficient $-0.036$ was both negative and statistically significant (see Table 5), suggesting that such dissimilar CEOs’ transition to overpay lowered ($p < .05$) the likelihood that the focal firm’s CEO will become overpaid.

The results strongly suggest that the “cognitive network” of peer groups–firms that may not have direct ties, but are considered similar in characteristics by CEOs and their board members–have a significant role in spreading high pay. Social comparison does not require explicit connection, and a rise in one firm can spread along to a CEO who considers himself/herself as managing a similar status firm, which leads to widespread diffusion of high pay in markets.

Relative to the educational and director networks, the peer benchmarking

11 Full GEE Estimates are available from the authors upon request.
models show a larger effect of volatility on pay. This effect is most likely due to the construction of the peer groups which may be similar in their volatility and pay, thus increasing the between peer effects of volatility.

5.2 Education

To adjudicate between the mechanisms of human capital and social contagion in explaining the diffusion of high pay, we investigate how social networks that arise from one’s educational background shape the likelihood that a firm’s CEO will become overpaid relative to the firm’s market value. Prior studies have found that CEOs who have attended elite schools receive higher levels of compensation, and educational connections are more influential on pay than professional or social ties that form later on in a CEO’s life (Engelberg, Gao, and Parsons, 2009). Education influences pay through multiple mechanisms. First, education signals superior talent to boards and external audiences. In addition, education affiliations increase the size of one’s external network, which has been shown to matter in labor markets (Engelberg, Gao, and Parsons, 2009). A third potential influence of education on pay is that school ties, similar to peer groups, serve as the basis for social comparison between CEOs, and lead to contagion of high pay practices.

Education networks are ideal in testing social contagion, since the direction of causality between tie and pay is less ambiguous. In other words, the significant time gap between educational attainment and pay decisions make it unlikely that intentions of high pay determine the selection into network relationships. More importantly, looking at pairs of CEOs within education networks allow us to conduct a more fine grained test on whether similar levels of talent is driving simultaneous increases in pay or social comparison is a more important mechanism.

More specifically, if CEOs with similar talent levels are more likely to have their pay move together, then a transition to overpaid status for one alumni should have a positive effect on the likelihood of the focal firm. Table 6 Models 1 through 5 replicate the GEE analysis with CEOs that graduated from the same school as alters. As seen in the results, the effect of Alter’s transition to high pay does not have a statistically significant effect on the transition of the focal CEO ($p > .05$).

While these results point to education networks playing a small role in a compensation setting, a closer analysis of the education network reveals a more nuanced picture. Rather than taking all alumni as alters that can influence the transition to high pay, Models 6 through 10 restrict the criteria for being considered an education alter to those who graduated within 10 years of the focal
CEO. The coefficient for Alter Currently Overpaid is over three times as large as the overall alumni network and statistically significant ($p < .05$), suggesting that those who are closer in graduation date exhibit strong tendencies for simultaneous transitions to overpay. This is consistent with the notion of social comparison as a mechanism, as one would expect similar cohort members to act as the most salient points of reference for pay comparisons.

5.3 Randomized Networks and Endogeneity Tests

Manski (1993) famously referred to the problem of endogenous effects in group influences as the “reflection problem” because it is hard to identify whether “the mirror image cause[s] the person’s movements or reflect them” (p. 532). In the context of CEO compensation, it is similarly possible that alters are not causing egos to transition to overpaid status, but rather, both are a reflection of broader social selection and context effects. While the above results strongly suggest that CEOs and boards are influenced by actors who are in the same social and cognitive networks, the relationship may be spurious.

We implement the randomization strategy outlined above for each of the social influences, and the results are shown in Model 11 for director networks, Model 6 for peer networks, and Model 11 for education networks.\textsuperscript{12}

In all three types of networks, the effect of the randomized alter’s overpaid state had no statistically significant effect on the likelihood that ego will transition to overpaid status. If the changing norms of CEO compensation was a broader social context effect, and not an influence that passes through the networks that tie organizations together, then one should observe a similar contagion-like effect for the re-wired network. The lack of effects in the randomized models suggest that the contagion effects we find are neither a statistical artifact of the model we employ, nor are they driven by an overall change in compensation practices.

It is important to note that the randomized networks do not themselves offer conclusive evidence regarding the issue of endogeneity. However, they provide a bench line assessment of how firms that are part of the broader field influence each other in pay, and a basis upon which our tests for endogeneity (i.e., latent networks) can be interpreted.

\textsuperscript{12}These models show the result of one shuffling of the alters. Averaged results from 1,000 randomization trials are available from the authors upon request.
6 Discussion

The above analysis estimated GEE logit models to compare three sources of social contagion: board interlocks, peer benchmarking, and education. Theoretically, we proposed that given the deep ambiguity surrounding the worth of a CEO, executive compensation would be influenced by social comparisons with similar others, once the effect of firm market value had been factored out. The initial estimations indicated that high pay diffused among CEOs through all three mechanisms. And indeed, past research has found that all three sources matter to CEO pay.

However, social networks are particularly susceptible to endogeneity issues. A social network can potentially reflect both selection and influence. Members who are linked through a social network may influence each other, but it is as well possible that they are linked because they are similar and share common predispositions and characteristics. In the case of executive pay, this conundrum takes the form of whether social contagion influences the diffusion of high pay, or if executives who evidence higher pay than predicted by a naive model are susceptible to common but unobserved effects, such as a shift in the demand for particular kinds of CEO talents.

This issue has become particularly salient in the context of the discussion in reference to the contagion models introduced by Christakis and Fowler, which we have also employed in our analysis. We have sought to strengthen the causal identification through two approaches. The first was to generate samples that randomized the network links among the CEOs for each of the three sources. While this randomization does not address selection bias, it provides a very intuitive and direct estimate of the network effect against a random baseline. In this regard, all three social network estimates are significantly different than the estimates derived against a randomized sample. This comparison can be seen visually in Figure 5 where the multiplier for the odds ratio of random is essentially 1 for all three social network randomizations; the coefficients for the social network variables are drawn from the fully specified models. Clearly, the estimate for peer benchmarking influence is the highest. The coefficient of the education network is close to the random model, whereas the result using a ten-year window is significantly higher, but considerably below the peer effect. Since the education network predates substantially promotion to the position of CEO, the danger of endogeneity is attenuated. Still, the overall size of the coefficient is significantly less than that for peer effects, using the Wald test given in Table 7.

The board interlock effect is of special interest given past studies showing network effects, including in the context of executive pay. The variable for shared directors among CEOs has a significant effect over the baseline random model.
However, sharing directors can be clearly a source of selection bias, since assortative matching between high quality firms, CEOs, and directors is likely to reflect prestige, status, or other unobserved sources of covariation. Indeed, through the construction of a "latent" network created by assuming a tie between boards before the tie actually existed, we were able to create a counterfactual. As seen in Table 7, a Wald test of the difference between the latent and true network estimations could not reject the null of no difference. This rejection of a social network echoes the conclusions reached by Van den Bulte and Lilien (2001) who found that marketing information, rather than social contagion, influenced adoption by doctors of a new pharmaceutical product.

The results of this paper indicate that the evidence for the influence of some kinds of social networks on a major decision of CEO pay is weaker than past studies in finance have shown. Board interlocks have two major structural weaknesses as channels of diffusion: the network is highly fragmented with many isolates and also some industries with high pay (notably banking) are not permitted to share directors by regulatory law. (As an aside, it should be recalled from Figures 3a and 3b, CEOs of financial firms are highly paid, but this higher pay is well explained by the larger size of financial firms.) Because educational networks are formed early in the lives of future CEOs, the dyadic pairing is less vulnerable to the reflection problem emphasized by Manski; however, it remains possible that, even after controlling for human capital, correlated error remains if educational affiliation is a proxy for individual quality differences. Our estimates indicate that an educational network effect is apparent for a narrow window of 10 years (meaning those CEOs who graduated within 5 years of the focal CEO and from the same institution), which strengthens the inference that education matters.

The results of the analysis point then with relatively higher confidence towards a peer benchmarking effect, which supports the emphasis placed by DiPrete, Eirich, and Pittinsky (2010) on social comparison to peers. Recall that peers were chosen using an estimated model from Faulkender and Yang (2010) that had access to the peer lists that companies filed with the SEC. We then used this model to predict the peers that would have been chosen by our sample. It is altogether possible that this methodology identified homophilous firms and/or CEOs and there is no cognitive network effect; it is simply correlated error. However, the criteria for these peer groups were quite diverse, including firms of similar sizes no matter their industry for example. Moreover, the peer groupings were not symmetrical, and a peer relationship was not necessarily reciprocated. In other words, it is not a priori obvious that peer groupings are subject to specific and shared economic shocks, although they, like all firms, are exposed to economy-wide disturbances.

Our results do not speak directly to the larger issue raised by DiPrete, Eirich, and Pittinsky (2010) if the choice of peers is biased to inflate CEO salaries,
thereby leading to a propagation of high pay and an upward trend in CEO pay. The propensity scoring method chooses firms of similar size, where the size range was bounded between one-half and twice the market value of the focal firm. To see if there is an ‘aspirational’ bias in social comparison, we also estimated an additional model, one where the bias was upward, with a range between 100% and 300%. Compared to the coefficient estimate of .286 given in model 6 for peer effects, the aspirational bias produces a coefficient of .313. This is in the direction of suggesting the ‘leapfrogging’ highlighted by Diprete, Eifrich, and Pittinsky, but the difference is not large. (Using more pronounced biases did not result in larger coefficient values.) At the same time, it should be recalled that the state variable of ‘high pay’ shows a positive time trend; it will be worthwhile to investigate further this variable trends upward.

6.1 Isolates and Finding the Critical Values

There remain two important issues to consider. The more mundane of the two is whether the omission of isolates from the GEE biased the estimates upward and misled the interpretation. Because of the dyadic construction of the GEE logit specification, CEOs who are not connected to another CEO are omitted. By definition, there can be no contagion in terms of the networked we identified. Still, this omission offers a nice test to see if contagion due to unobserved factors (such as common economic shocks) might matter. In Figure 6, we first show the percentage of isolates for each of the networks. We then compare the proportion of over-paid of the isolates against proportion for the connected firms. The Mantel-Haenszel non-parametric test shows the null hypothesis of no difference is rejected for all three networks, supporting an inference that the isolates’ lower proportions results from the deprivation of network (and homophilous) effects.

The more interesting issue returns us to the earlier observation of Shalizi and Thomas if the feedback effect leads to unreasonable results. Our argument is that a shift in social norms and through a mechanism of social comparisons lead to an increase in CEO pay beyond what is predicted by the economic assortative talent model. Nevertheless, this tendency of increasing over-pay against this benchmark can lead to a prediction that CEO pay will eventually absorb an unsustainable proportion of the market economy. However, while this prediction does arise if the focus is only on the positive coefficients to the egocentric and altercentric variables, the negative coefficients to the CEO tenure and mobility variables dampen these effects.

To be more precise, we built an agent-based model (ABM) of the competing effects of the positive feedback from the network effects and the negative effects from the mobility effects. The nodes are the CEOs and the links are
their ties (created by the projections from the bipartite graphs); isolates are also included. We created three different simulations for each of the three types of networks (director, peers, and education) using the empirical data.

The state variable is whether a CEO node is over- or underpaid. Initially, 40% of nodes are randomly chosen to be assigned $S = 1$ and the rest of nodes are assigned $S = 0$ using the 1997 data. The ABM begins with these initial values, which trigger a contagion among the networked nodes governed by the transition probabilities and parameter values. This process proceeds in four steps:

(1) **Diffusion through the networks.** As shown in the Figure 7a, a CEO with many ties is more likely to be overpaid. Using this fact, we modeled the transition rate of the overpaid state. We calculate the transition probability for any ego of state value 0 as $p_N = 1 - (1 - \alpha)^s$, where $\alpha$ is a diffusion factor and $s$ is the number of neighboring CEOs who are overpaid. For higher $\alpha$ and $s$, the state of CEO is more likely to be overpaid.

(2) **Tenure.** The state is also sensitive to the CEO’s tenure. Tenure of CEOs is also initialized by the distribution of tenure shown in the upper panel of Figure 7b. As shown in the figure, the proportion of overpaid CEOs increases as the tenure increases up to 10 years and then the proportion decreases after 10 years; we ignore the outliers with few observations after 30 years. From this observation, we defined the transition rate by tenure as $p_T(t) = -\beta(t - 10)$ for $t < 20$ and $p_T(t) = 0$ otherwise, where $t$ is tenure and $\beta$ is a parameter to adjust the sensitivity to the tenure.

(3) **CEO change.** CEOs change due to retirement, turnover (e.g. termination or departure), or death of the previous CEOs. With probability $\delta$, CEO is replaced by a new CEO whose state is overpaid with probability $\gamma$. To simplify the model, and to fit the empirical data, the overpaid new CEO is regarded as an outsider and underpaid new CEO as an insider. For insiders, tenure is reset to 0.

(4) **Transition rate.** Finally, the transition rate for the update of state is defined as $p = p_N + p_T$. Each year, every node is updated to the overpaid state with probability $p$.

The central objective of the simulation is to calculate the critical values to the parameters which would predict that the contagion process converges to excessively high and sustained proportion of overpaid CEOs. Though it is reasonable to think that an external shock may move CEO pay out of equilib-

---

13 Because the overpaid state diffuses with probability of $\alpha$ another node to which it is tied, $(1 - \alpha)^s$ is be the probability that a node is not contaminated by $s$ overpaid neighbors; consequently, a node would be contaminated with probability $1 - (1 - \alpha)^s$.

14 The longest tenure is 59 years: Walter J. Zable who is 93 year old at 2010 and has been CEO of Cubic Corp. since 1951.
rium, there are also competitive labor market forces (namely, CEO mobility and replacement) that dampens these effects. In the simulations described below, we find the following parameter values to approximate best the empirical data: the $\alpha$ values to 0.03 (five times this value for peers), $\beta$ to 0.05, $\gamma$ to 0.6 and $\delta$ to 0.1.

Figure 8a shows the sensitivity of pay to the tenure parameter $\beta$, fixing the other parameters to the above values. The $\beta$ parameter adjusts the heterogeneous growth tendency of compensation by tenure. The higher the value of $\beta$, the higher is of course the evolution of the overpaid state. According to the empirical data, the compensation level of new CEOs increases, but it decreases for incumbent CEOs whose tenure is more than 10 years. By adjusting $\beta$, the sensitivity of compensation to the tenure can be seen to be very elastic up to 10 years and then flattens out. Above a certain value of $\beta$, the proportion of compensation does not increase. As shown in Figure 9, 0.1 is a critical value, above which overpay tends to increase to up 80% or more of the CEOs. The mean value of tenure in the data implies a $\beta$ of about .05, which has the reasonable prediction of overpay of about 55%. The simulation is close to the prediction of the estimated model and also shows the importance of tenure to dampening the dynamics of the model. It is reassuring that these parameter values of $\beta$ do not lead to an explosion to 100% overpay.

Another way that network effects may be dampened is through more frequent external hiring. If pay deviates from a long-term trend, the market for CEOs is likely to incur entry and more competition, raising the rate of external hiring. Figure 8b shows the variation of the proportion of overpaid state at the year of 2009 by varying $\delta$, which indicates the proportion of CEO replacements who come from outside the firm. As $\delta$ increases, the proportion of overpaid state also increases, but it decreases after $\delta$ reaches 0.10. Interestingly, $\delta = 0.10$ is close to the proportion of CEO change from the empirical data. The counter-intuitive implication is that the impact of external hiring on CEO pay peaks at close to the empirically-observed values, and further rates of external replacement then dampens excess pay. The model dynamics therefore appear to be consistent with a long-run return to a stable steady-state. A phenomenon of ‘leap-frogging’ or ‘network contagion’ is bounded by the dynamics of the market for CEOs. Thus, the estimated model is compatible with a comforting logic that the long-run stabilizes, even if in the interim, CEOs earned considerably higher pay relative to the economic model. In other words, short-term shocks can shift the expectations regarding pay which diffuses through social comparisons among peers.

If we return to Figure 1, the following inference is suggested: the internet boom in market values of public firms at the turn of the century lead to an increased expectations as to acceptable pay, and this shift in norms then percolated from these core internet industries, such as telecomm, to the rest
of the economy through social comparisons. This pattern of a shift in pay over the previous relationship to market value is consistent with the results of the above estimations. To investigate this speculation, we estimated the Gini coefficient of inequality over the time span of our study. The Gini value is .26 in 1994 and then rises to .40 in 2000, falling back to the previous levels (.28) in 2002 and even lower during the financial crisis. This massive shock to CEO pay during the internet boom shifted broadly expectations and social norms, which then percolated by social comparisons among CEOs and board in subsequent years.

6.2 Conclusions

The stunning increase in CEO pay in excess of the increase in the market valuation of public firms poses the question how did this change percolate among a population of CEOs. It could be reasonable, even if unproven, that the job of the CEO has become more difficult in the past decades, requiring a heightened scarcity value placed upon talent. The approach we took above permits pay to vary by economic trends and shocks that feed into the market values of firms. Moreover, we conditioned the contagion effect on the CEO’s egocentric characteristics by incorporating the previous state description of under-pay and over-pay.

Then what do peer and educational networks do? The utility of social networks is not only to channel job information (as in the tradition of Granovetter’s seminal insight (Granovetter, 1973) on the strength of weak ties in job search), but also to set expectations that resolve egocentric and altercentric uncertainty over worth. In this regard, social networks, by directing social comparisons among salient peers and educational cohorts, supply an important mechanism for the change in social norms. In this role, the change in norms by contagion adds a micro-macro element of dynamism to the observation that values are justified by different orders of worth (Boltanski and Thévenot, 1992). Justification of ‘fair pay’ and expectations around ‘reservation prices’ changes through exogenous pay increases for some executives that percolate through these networks by a process of social comparison. White observes that social identities flow through networks. These relational identities are not embedded in, but constitute markets; they are the directional arrows to the making of social comparisons (White, 1992).

Apart from a shift in norms and increased demand for specific talent, another explanation for the increased share of income earned by executives is the deterioration in countervailing social institutions, such as labor. The particular decline of these institutions in the United States is surely a candidate explanation for the rapid increase in executive compensation and growing income
inequality, a point emphasized by McCall and Percheski (2010). Western and Rosenfeld (2011) show that the decline of unionism in the US explained one-third to one-fifth of the increase in wage inequality, which they attribute to an erosion of social norms. This decline is likely a factor that enables the diffusion of shifting norms by eliminating the possibility of sanctions, and this is thus a necessary complement to the function played by social networks in influencing normative notions of worth.

There is still a troubling aspect to theories, such as that of leapfrogging proposed by Diprete et al., regarding the long-term implications. Clearly, there must be a ceiling to the amount of corporate income that can be paid to top executives. It would be convenient to believe that the labor market of CEOs quickly reverts to a long-term sustainable equilibrium, as in the talent model by Gabaix and Landier (2008). However, a pairwise comparison among executives does not guarantee a global equilibrium, as most studies in the network economics of labor markets have noted (see Jackson, 2008).

It seems plausible, as our simulations have suggested, that social dynamics could produce short-term deviations that cumulatively instigate a trajectory that departs from socially-preferred or economically viable outcomes. The sustainability and viability of increasing CEO pay pose complex economic and political questions. The simple insight offered by the finding that high pay diffuses by contagion through social networks is the observation that reasonable local rules relying on social comparison to set pay may not lead to social and economic macro-outcomes that are desirable or stable in the duration of time. However, even if the rules are endogenously recalibrated to return to more historical proportions, the accumulation of wealth during this interim period will remain an enduring source of inequality, along with the correlated effects on derived income and political influence.
References


Barnea, A. and I. Guedj. 2006. “But, Mom, All the Other Kids Have One!—CEO Compensation and Director Networks.” McCombs school of business working paper, University of Texas at Austin.


Liang, K. Y and S. L Zeger. 1986. “Longitudinal data analysis using general-
ized linear models.” *Biometrika* 73:13.


Fig. 1. Composition of Executive Pay

Fig. 2. Cumulative distribution of Director Degree (Ties) over Time
Fig. 3. Regression fit of log market value to log compensation.
Fig. 4. Comparison of Two Intra-Industry Board Interlocks

(a) Electronics

(b) Bank
Fig. 5. Increase in Odds Ratio of Overpay for Ego based on Type of Alter. Error bar is 95% of conf interval.
Fig. 6. The proportion of isolates (a) and the proportion of overpaid CEOs (b-d) for each of networks.
Fig. 7. Sensitivity of the proportion of overpaid CEOs to (a) degree of director network and (b) tenure.
Fig. 8. Realization of proportion of overpaid COEs by agent based computational simulations; variation of (a) $\beta$ and (b) $\delta$. 

(a) 

(b)
Fig. 9. Temporal evolution of the proportion of overpaid CEOs by varying $\beta$. 
<table>
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<td>University of Chicago</td>
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<td>1.3</td>
<td>281</td>
<td>586.58</td>
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Table 1. Average compensation, proportion of overpaid CEOs, and average residual by education institution.
Table 2  
Descriptive statistics

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### Table 3. Correlation.

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<td>(7) EBIT</td>
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<td>0.318</td>
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## Table 4
Logit Estimates of Likelihood of Overpay for Board of Director Ties (GEE specification with year fixed-effects and standard errors in parentheses)

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<td>(3)</td>
</tr>
<tr>
<td></td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td>Previously Overpaid</td>
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<td>1.596**</td>
<td>1.629**</td>
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<tr>
<td></td>
<td>(0.071)</td>
<td>(0.071)</td>
<td>(0.074)</td>
</tr>
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<td>Alter Currently Overpaid</td>
<td>0.105**</td>
<td>0.068**</td>
<td>0.072**</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.025)</td>
<td>(0.025)</td>
</tr>
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<td>0.202</td>
<td>0.225</td>
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<td>(0.273)</td>
<td>(0.257)</td>
<td>(0.260)</td>
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<td>Tenure</td>
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<td>-0.005</td>
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<td>Change in CEO</td>
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<td>-1.183**</td>
<td>-1.092**</td>
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<td>(0.103)</td>
<td>(0.103)</td>
<td>(0.107)</td>
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<td>1.568**</td>
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<td>(0.477)</td>
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<td>0.098</td>
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<td>Wald $\chi^2$ (df)</td>
<td>805.56(13)</td>
<td>818.11(14)</td>
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* $p < 0.05$, ** $p < 0.01$
Table 5
Logit Estimates of Likelihood of Overpay for Peer Group Ties (GEE specification with year fixed-effects and standard errors in parentheses)

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<td>(6) (7)</td>
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<td>Ego Previously Overpaid</td>
<td>1.646** 1.618** 1.596** 1.917** 1.914** 1.801** 1.939**</td>
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<td>Alter Currently Overpaid</td>
<td>0.361** 0.302** 0.296** 0.299** -0.036** 0.066</td>
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<tr>
<td>Gender (0:Male 1:Female)</td>
<td>1.113** 1.075** 1.094** 0.318 1.103**  0.345</td>
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<td>Tenure</td>
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<tr>
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<td>New CEO is Outsider</td>
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<td>Human Capital</td>
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<td>Constant</td>
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<tr>
<td>Observations</td>
<td>13114 13114 11235 11235 11235 165035 11235</td>
<td></td>
</tr>
<tr>
<td>Wald χ² (df)</td>
<td>419.89(13) 444.49(14) 412.63(17) 446.60(19) 448.12(20) 686.04(20) 440.26(20)</td>
<td></td>
</tr>
<tr>
<td>Prob &gt; χ²</td>
<td>0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000</td>
<td></td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01
Table 6. Logit Estimates of Likelihood of Overpay for Education Ties (GEE specification with year fixed-effects and standard errors in parentheses)

<table>
<thead>
<tr>
<th></th>
<th>Education network</th>
<th></th>
<th>Education network (10 years)</th>
<th></th>
<th>Random network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ego Previously Overpaid</td>
<td>1.702**</td>
<td>1.702**</td>
<td>1.842**</td>
<td>2.093**</td>
<td>2.081**</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.104)</td>
<td>(0.113)</td>
<td>(0.128)</td>
<td>(0.127)</td>
</tr>
<tr>
<td>Alter Currently Overpaid</td>
<td>0.006</td>
<td>0.015</td>
<td>0.020</td>
<td>0.018</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>Gender (0:Male 1:Female)</td>
<td>-0.199</td>
<td>-0.168</td>
<td>-0.126</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.469)</td>
<td>(0.425)</td>
<td>(0.395)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tenure</td>
<td>-0.011</td>
<td>-0.007</td>
<td>-0.007</td>
<td>-0.009</td>
<td>-0.006</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.009)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Volatility of Stock</td>
<td>3.289</td>
<td>2.939</td>
<td>2.875</td>
<td>4.822</td>
<td>3.933</td>
</tr>
<tr>
<td></td>
<td>(3.002)</td>
<td>(2.962)</td>
<td>(2.941)</td>
<td>(3.799)</td>
<td>(3.741)</td>
</tr>
<tr>
<td>Change in CEO</td>
<td>-1.202**</td>
<td>-1.194**</td>
<td>-1.171**</td>
<td>-1.165**</td>
<td>-1.178**</td>
</tr>
<tr>
<td></td>
<td>(0.160)</td>
<td>(0.159)</td>
<td>(0.169)</td>
<td>(0.169)</td>
<td>(0.148)</td>
</tr>
<tr>
<td>New CEO is Outsider</td>
<td>0.673</td>
<td>0.690</td>
<td>1.587*</td>
<td>1.583*</td>
<td>0.687</td>
</tr>
<tr>
<td></td>
<td>(0.652)</td>
<td>(0.627)</td>
<td>(0.653)</td>
<td>(0.644)</td>
<td>(0.525)</td>
</tr>
<tr>
<td>Human Capital</td>
<td>0.259*</td>
<td></td>
<td></td>
<td>0.102</td>
<td>0.190</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td></td>
<td></td>
<td>(0.107)</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.146**</td>
<td>-1.149**</td>
<td>-1.153**</td>
<td>-1.177**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.182)</td>
<td>(0.182)</td>
<td>(0.226)</td>
<td>(0.219)</td>
<td>(0.229)</td>
</tr>
<tr>
<td>Observations</td>
<td>150482</td>
<td>150482</td>
<td>118885</td>
<td>118885</td>
<td>118885</td>
</tr>
<tr>
<td>Wald χ² (df)</td>
<td>354.12(13)</td>
<td>354.92(14)</td>
<td>343.55(17)</td>
<td>351.23(19)</td>
<td>352.87(20)</td>
</tr>
<tr>
<td>Prob &gt; χ²</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

* p < 0.05, ** p < 0.01
Table 7
Comparison of alter effects

| Network I  | Network II | $|z|$ | $P > |z|$ |
|------------|------------|------|----------|
| Director   | Latent     | 0.58 | 0.563    |
| Director   | Peer       | 4.39 | 0.000    |
| Director   | Edu (10 yr.) | 0.50 | 0.614    |
| Peer       | Edu (10 yr.) | 4.33 | 0.000    |