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MANAGERIAL ATTRIBUTES AND EXECUTIVE COMPENSATION

John R. Graham
Si Li
Jiaping Qiu

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ABSTRACT

We study the role of firm- and manager-specific heterogeneities in executive compensation. We decompose the variation in executive compensation and find that time invariant firm and especially manager fixed effects explain a majority of the variation in executive pay. We then show that in many settings, it is important to include fixed effects to mitigate potential omitted variable bias. Furthermore, we find that compensation fixed effects are significantly correlated with management styles (i.e., manager fixed effects in corporate policies). Finally, the method used in the paper has a number of potential applications in financial economics.

John R. Graham
Duke University
Fuqua School of Business
100 Fuqua Drive
Durham, NC 27708-0120
and NBER
john.graham@duke.edu

Si Li
School of Business and Economics
Wilfrid Laurier University
Waterloo, ON
N2L 3C5, Canada
sli@wlu.ca

Jiaping Qiu
DeGroote School of Business
McMaster University
Hamilton, ON
L8S 4M4, Canada
qiu@mcmaster.ca

1. Introduction

Executive compensation is of considerable interest to the business and academic communities, as well as to policymakers. The existing literature documents that observable firm characteristics (e.g., firm size and performance) and managerial characteristics (e.g., job tenure and gender) partially explain the variation in executive pay. However, little is known about the impact on compensation from unobservable firm and managerial characteristics, such as latent managerial skills.[1] In this paper, we study the direct influence of firm and manager fixed effects on executive compensation, as well as how the inclusion of fixed effects impacts the interpretation and contribution of traditional explanatory variables.

In terms of the direct influence of fixed effects, it is well known that observationally equivalent individuals often earn markedly different levels of compensation. This could occur because of unobservable firm characteristics, such as corporate culture, or it could be due to unobserved personal characteristics, such as innate ability or personality. This suggests that it is important to directly examine whether unobservable firm and manager characteristics could explain a significant portion of the variation in executive compensation.[2] In terms of the impact on the significance and interpretation of other explanatory variables, to the extent that excluded person or firm effects are correlated with observable characteristics, empirical analysis of the latter could produce biased coefficient estimates. For example, highly skilled managers are more likely to be paid higher wages; such managers could also tend to work in

[1] Consistent with the statistics and economics literatures, we use the word “unobservable” to indicate information that is difficult to quantify or unavailable to the econometrician—hence it is “unobservable” from the perspective of the econometrician. We do not exclude the possibility that such “unobservable” information may be observed by other parties such as employers.

[2] As discussed later, we use fixed effects to capture the time-invariant dimension of unobserved heterogeneity. It is possible that some unobserved heterogeneities can change over time; the fixed effects model cannot capture such time-variant unobserved heterogeneity.

larger firms. In models that do not account for manager fixed effects, the estimated effect of firm size on executive pay could be inflated.

Several approaches could be used to address the primary goal of this paper, which is to investigate the role of unobservable time-invariant firm and manager heterogeneities (or, loosely speaking, firm and manager fixed effects) in determining executive pay.[3] The simplest approach combines firm and manager fixed effects by including a dummy variable for each unique firm-manager combination (which is called a "spell") in the full universe of compensation data. This "spell fixed effects" approach controls for the combined influence of firm and manager fixed effects, and mitigates possible concerns about estimation bias. However, the spell approach does not separately identify firm and manager fixed effects and thus does not reveal their relative importance. Therefore, the spell approach is not adequate to address an additional goal of our paper, which is to isolate and quantify how much of the variation in executive pay is attributable to observable time variant firm effects (e.g., firm size, market to book ratio, firm performance), observable time variant manager effects (e.g., job tenure), time invariant firm fixed effects, time invariant manager fixed effects, and year effects.

One way to separately identify these various effects is to study a panel of compensation data composed only of managers who have changed firms and to include manager, firm, and year dummies in the specification. For example, Bertrand and Schoar (2003) use this approach to study how manager fixed effects are related to various corporate activities. We refer to the approach of studying a sample of managers who have changed firms as the MDV (mover dummy variable) method. The sample that can be studied using the MDV approach, however,

[3] Time-invariant or slow moving manager heterogeneity, such as latent managerial ability, will be captured by manager fixed effects. For example, Abowd et al. (1999, 2003) and Iranzo et al. (2008) use person fixed effects to proxy for employee human capital. However, it is also possible that managers may develop their abilities over time. We attempt to capture time changing managerial ability by including job tenure in our empirical specifications.

is necessarily small due to the relatively small number of executive job changes in most samples. Because of this limitation, we introduce to the finance literature an alternative method to estimate manager and firm fixed effects separately. This alternative method is based on Abowd, Kramarz, and Margolis (1999; AKM henceforth). The AKM method can lever the potentially small number of mover observations (i.e., managers who move across companies) to deduce information about non-movers who work in firms that have employed at least one mover. This allows us to separate firm and manager fixed effects not only for movers but also for some non-movers, increasing the sample size and power.

The key economic implications from our paper are similar regardless of whether we use the spell method, the MDV method or the AKM method. We consistently find that firm and manager fixed effects explain a significant proportion of the variation in executive compensation. When separating manager fixed effects from firm fixed effects using either the MDV or the AKM method, we find that manager fixed effects are more important than firm fixed effects in explaining the level of executive pay. We also demonstrate that ignoring fixed effects could yield biased coefficient estimates for other variables. For example, we find that the magnitude of the firm size coefficient decreases by approximately 40% when manager fixed effects are included in the specification. Our results suggest that in many settings it may be important to control for manager and firm fixed effects to mitigate missing variable bias.[4]

We also link our estimates of manager fixed compensation effects to management "styles" in corporate policies. We study whether managers with different styles or traits are remunerated accordingly. According to Bertrand and Schoar (2003), managers vary in style

[4] Our analysis does not imply that every empirical specification should include firm and manager fixed effects. The decision of whether or not to employ a fixed effects model is predicated on the goal of the research. It is worth noting that the fixed effects model is not without limitations. We discuss caveats and interpretation issues in detail at the end of Section 4.1.3.

and differ in the aggressiveness of their investment and financing choices. Our finding that links policy fixed effects and compensation fixed effects indicates that more aggressive managers appear to be remunerated for the additional risk they take.

The primary contributions of this paper are threefold. First, the paper adds to the executive compensation literature by providing the first empirical study of the role of unobserved firm and managerial heterogeneities in determining executive pay. The literature on executive compensation (Core, Holthausen, and Larcker, 1999, Core, Guay, and Larcker, 2008, Frydman and Saks, 2010, Gabaix and Landier, 2008, Rose and Shepard, 1997, among others) has focused on how observable firm and manager characteristics affect the level of pay. Many of these studies do not include any fixed effects, some include firm fixed effects, very few include manager fixed effects, and none include both.[5] Given the importance of latent factors such as innate ability, preferences, risk aversion, personality, firm culture, etc. in shaping corporate outcomes, we view incorporating both firm and manager heterogeneities into the determinants of executive pay as a significant step. When quantifying the explanatory power of the time-invariant dimension of these heterogeneities, our results suggest that firm fixed effects and particularly manager fixed effects are important factors in explaining executive pay.

Second, to the extent that the omitted relevant variables are time invariant, including both firm and manager fixed effects produces estimated parameters on observable firm and managerial characteristics that are less likely to be contaminated by omitted variable bias. Most prior research focuses on the observed characteristics in order to address particular theories.

[5] When regressing the level of executive pay on explanatory variables, some papers control for firm fixed effects (Bertrand and Mullainathan, 2001, Chhaochharia and Grinstein, 2009, Frydman and Saks, 2010, Gabaix and Landier, 2008, Hubbard and Palia, 1995, Joskow et al., 1996, Kraft and Niederprum, 1999, Perry and Zenner, 2001), a few papers control for manager fixed effects (Aggarwal and Samwick, 1999, Garvey and Milbourn, 2003, Perry and Zenner, 2001), and none control for both at the same time. All these prior studies focus on observable determinants.

We point out that to interpret the evidence in the context of theories, it is important to control for fixed effects if doing so helps mitigate potential omitted variable bias. For example, the significant relation between firm size and pay is well established in executive compensation. We show that the effect of firm size on executive pay level is likely overstated if the omitted variables are not properly controlled. Our paper also documents the economic effects of manager fixed effects by showing that they are significantly related to corporate policies.

Our third contribution is the introduction of the AKM method into finance, in the context of the growing attention being paid to manager-specific effects. Bertrand and Schoar (2003) examine managerial fixed effects in corporate activities such as return on assets, investment, leverage, and cash holdings.[6] However, their MDV method is only used on a relatively small dataset, while the AKM method can separately identify manager fixed effects from firm fixed effects for a much larger set of executives. The typically used spell method also has limitations. Frank and Goyal (2007) find that adding manager fixed effects to a regression analysis of the determinants of leverage significantly increases the model fit.[7] However, the spell fixed effects method cannot disentangle manager from firm fixed effects. As a result, the exact power of manager fixed effects in explaining leverage variation is unclear.

The AKM method avoids the shortcomings of the other two methods and has broad potential in many finance and accounting research areas where capturing firm- and manager-specific effects is desirable. For example, one could examine manager and firm fixed effects in various corporate activities, which include but are not limited to corporate investment and financial policies, and earnings management, among others (Coles and Li, 2011a, 2011b). Or

[6] Bertrand and Schoar (2003) do not investigate managerial fixed effects in compensation, though they do find that managers with higher return on assets manager fixed effects have greater excess compensation.

[7] Lemmon et al. (2008) study the role of firm fixed effects (not manager fixed effects) in determining leverage and find that firm fixed effects are an important factor in explaining leverage.

one may be interested in separately investigating mutual fund manager fixed effects and fund company fixed effects in mutual fund performance, or analyst fixed effects and brokerage firm fixed effects in earnings forecasts.

Our results should be interpreted with two points in mind. First, fixed effects may lead to over-controlling if some determinants of executive pay move slowly through time. That is, if the explanatory variable of interest mainly varies cross-sectionally, then fixed effects could absorb the variation of interest. The fixed effects approach is more suitable when the explanatory variables of interest present sufficient time series variation. Second, the fixed effects model provides a simple method to address the omitted variable bias issue if omitted variables or unobserved factors are time constant or slow moving. However, fixed effects are unable to solve the omitted variable problem or the selection problem caused by time-variant unobserved factors.

The rest of the paper proceeds as follows. The next section discusses the empirical methodology; the Appendix B explores related statistical issues in greater detail. Section 3 describes the data, variables, and summary statistics. Results, implications, and robustness tests are given in Section 4. The last section concludes.

2. Empirical Methodology

2.1 A Three-Way Fixed Effects Model of Compensation

To motivate the empirical specification, first consider a simple model of human capital in the spirit of Becker (1993) and Mincer (1974). Let HC_{it} denote manager i's stock of human capital at time t, while U_t denotes the time t rental rate of human capital. Hence, the individual's expected wage rate y_{it} can be determined as

$$y_{it} = U_t \times HC_{it} \ . \tag{1}$$

Assume that human capital is reflected in the observable firm and manager characteristics, W_{jt} and X_{it}, and the latent firm and person specific inputs, φ_j and θ_i. Then the exponential form of production function gives

$$HC_{it} = e^{X_{it}\beta + W_{jt}\gamma + \varphi_j + \theta_i} \ . \tag{2}$$

Combining equations (1) and (2) and taking the logarithms yields the standard human capital log wage function as

$$Ln(y_{it}) = X_{it}\,\beta + W_{jt}\,\gamma + \varphi_j + \theta_i + \mu_t\,, \tag{3}$$

where $\mu_t = Ln(U_t)$. Adding an error term ε_{it} to the theoretical equation (3) gives the empirically estimable equation

$$Ln(y_{it}) = X_{it}\,\beta + W_{jt}\,\gamma + \varphi_j + \theta_i + \mu_t + \varepsilon_{it}\,. \tag{4}$$

Equation (4) indicates that an executive's expected compensation is the sum of the market valuation of his or her personal characteristics $X_{it}\beta+\theta_i$ (observable and unobservable), the specific compensation policies $W_{jt}\gamma+\varphi_j$ chosen by the executive's employer (observable and unobservable), and time effects in compensation μ_t. Residual ε_{it} reflects a manager's residual compensation, which captures the compensation that is not priced in the labor market given a manager's observable and unobservable human capital. This model assumes that for any given manager i, θ_i is constant over time, whether the manager stays in the same firm or moves to a new employer. Consistent with Frydman (2007) and Murphy and Zabojnik (2004, 2007), managers' general skills that are transferable across companies can be captured by θ_i.[8] The time-invariant component φ_j of firm-specific compensation policies could reflect the time-

[8] Managerial ability is just one interpretation of manager fixed effects θ_i. θ_i could capture managerial traits other than ability as long as these traits are time invariant or slow moving.

invariant dimension of corporate monitoring or incentive considerations or the compensation premia in firms with persistently abnormal profit (Abowd et al., 2003).

In model (4), there are three fixed effects: manager fixed effect θ_i, firm fixed effect φ_j, and year fixed effect μ_t. This three-way fixed effects model is our main specification throughout the paper. The model provides a way to mitigate the omitted variable bias common in our applications if the relevant omitted variables are primarily time invariant. For example, firm size, an explanatory variable frequently used in finance, is likely correlated with manager-specific innate ability and firm-specific corporate policies. In a model that does not capture both manager and firm fixed effects, the unobserved person and firm heterogeneities are absorbed into the error term ε, causing correlations between the error term and explanatory variables. Such correlations violate the exogeneity condition and lead to inconsistent and biased estimates of β and γ. The fixed effects model, by separating unobserved time invariant heterogeneities from the error term, provides consistent, unbiased, and generally efficient estimates of β and γ, as long as the error in (4) is uncorrelated with observable characteristics (X and W) and fixed effects (θ, φ, and μ). Model (4) also allows fixed effects themselves to be arbitrarily correlated with explanatory variables X and W (Wooldridge, 2001).

2.2 Estimation Methods

2.2.1 Spell Fixed Effects Method

The spell method creates a dummy variable, V_s, for each unique combination of manager i and firm j (i.e., for each spell). The spell level heterogeneity V_s is equal to $\varphi_j + \theta_i$, and Equation (4) can be rewritten as $Ln(y_{it}) = X_{it}\,\beta + W_{jt}\,\gamma + V_s + \mu_t + \varepsilon_{it}$. The model is thus reduced to a two-way fixed effects model and can be estimated on the full sample using standard fixed effects approaches, which include the within approach and the least square dummy variable (LSDV) approach. The spell approach has been used in the literature (Abowd et al., 1999, Munch and Skaksen, 2008, and Schank et al., 2007) to control the influence of manager and firm fixed effects in a manner that addresses possible omitted variable bias. However, using this approach, one can only estimate the joint manager-firm fixed effects V_s and cannot separately identify φ_j and θ_i. To separate the firm from manager fixed effects, one should use the MDV method or the AKM method, which are discussed below.

2.2.2 The Mover Dummy Variable (MDV) Method

We are interested in not only controlling for unobserved manager θ_i and firm φ_j fixed effects but, in some parts of the analysis, we are also interested in estimating the magnitudes of each fixed effect separately. Intuitively, if a company has no managerial turnover during the sample period, the firm's fixed effect cannot be disentangled from the fixed effects of its managers because the two effects are perfectly collinear. Therefore, the separation of manager fixed effects from firm fixed effects is only possible when the firm has at least one mover (i.e., a manager who switches companies). The mover dummy variable (MDV) method used in Bertrand and Schoar (2003) restricts the sample to movers, includes dummy variables for each manager and each firm, and then estimates Equation (4) using the least square dummy variable (LSDV) approach.

One disadvantage of the MDV approach is that managers who have moved could be different from managers who never change firms, and the resulting sample selection bias could limit the generalizability of the results. Another disadvantage is that this method may face computer limitations related to inverting a matrix with many dummy variables in very large samples (see Appendix B.1 for details). This second disadvantage is less significant unless the dataset is quite large. Due to these limitations, in the next section we introduce an alternative method to separate the fixed effects.

2.2.3 The Abowd, Kramarz, and Margolis (AKM) Method

The alternative method we use to separate firm from manager fixed effects is based on Abowd, Kramarz, and Margolis (1999). The AKM method, by identifying manager and firm fixed effects through *group connection*, allows us to separate firm and manager fixed effects not only for movers but also for non-moving executives, as long as the non-movers work in firms that have hired at least one mover. Group connection is defined as follows. Start with an arbitrary individual and include all the companies for which he or she has ever worked. Next, add all the individuals who have ever worked in any of those companies. Continue adding all additional firms for which any of these individuals has ever worked and all additional individuals in any of those firms until no more individuals or firms can be added to the current group. Repeat for the next group and continue until all data are exhausted. Hence, every person and firm belongs to exactly one group and within every group all the persons and firms are connected somehow. The detailed algorithm of forming groups can be found in Abowd et al. (2002). We discuss the technical details of the AKM method in Appendix B.

Connectedness is related to, but is not identical to, mobility. A manager who has never moved can be connected to another company as long as at least one other manager in his or her firm has worked at the other company. Therefore, a small amount of mobility can generate a large amount of connectedness. Within each group, there is person mobility, which connects persons and firms in this group. Between groups, there is no mobility. Abowd et al. (1999) formally prove that connectedness is necessary and sufficient for the separate identification of person and firm fixed effects. Mobility, a requirement of the MDV method, is sufficient but is not a necessary condition.

Although only a moderate proportion of managers have changed firms in our sample, these turnovers allow us to separate a large number of manager and firm fixed effects through group connection. We refer to this larger sample retained by the AKM method as the *connectedness sample*, while the sample used in the MDV method that includes only movers is called the *mobility sample*. Note that these two samples contain the same firms. The mobility sample includes only movers from these firms, while the connectedness sample includes both movers and non-movers in these firms. One benefit of the larger connectedness sample is the increased precision of the model estimates (see Appendix B.2 for details).

Abowd et al. (2004) and Andrews et al. (2008) show that when worker mobility is limited, there may be estimation bias that causes the person and firm effects to be estimated imprecisely. The intuition is that we use the mover information to figure out the firm fixed effects. When the number of movers goes up, we have more information and thus the firm fixed effects (and then the manager fixed effects) can be estimated more precisely. The limited mobility bias is present in both the MDV and the AKM methods because both methods depend on the mover information to identify the fixed effects. Consequently, the results for both MDV and AKM need to be interpreted with this limitation in mind.

Below, we start by using the spell method in the full sample, then use AKM as our primary method to disentangle manager and firm fixed effects in the connectedness sample. We use MDV on the mobility sample to test the robustness of the results.

3. Data and Summary Statistics

3.1 Sample Selection

Our sample consists of a matched ExecuComp-Compustat panel dataset from 1992 to 2006. This dataset allows us to track through time the highest paid executives in firms covered by ExecuComp. We merge the manager-level ExecuComp data with firm-level annual accounting variables from Compustat and firm-level stock returns from CRSP. We then remove observations with incomplete data. Our full sample includes 25,586 managers who have worked for 2,344 firms. When we use the spell method to control for the influence of unobserved firm and manager heterogeneities, we estimate based on this full sample.

Because managerial mobility or connectedness is necessary to permit the separation of manager fixed effects from firm fixed effects, Table 1 presents information on the movers and stayers in our sample. Panel A shows that during the sample period from 1992 through 2006, 4.9% or 1,256 managers are movers who worked as top executives in more than one company in the sample, while the rest (95.1%) are non-movers who worked in a single sample firm.[9]

[Table 1 about here]

Panel B provides information on the proportion of companies that have a given number of top managers who move during the sample period. About 45% of the sample firms do not have any managers who move across companies, while the remaining 55% (1,272 firms) have manager switchers. We are able to identify fixed effects for all the managers who are or were in these 1,272 firms, irrelevant of whether they move or not. When we want to separately identify manager fixed effects from firm fixed effects using the AKM method, we perform our analysis on the subsample of the firms (i.e., 55% of the full sample) in which there are movers. This "someone at the firm moved" sample (i.e., connectedness sample) includes 15,352

[9] Note that we are only able to capture managers' movements within ExecuComp firms. It is possible for a manager to move to or from a firm that is not in the sample; we are unable to trace such activity due to data limitations.

managers who have worked for 1,272 firms. The mobility sample (analyzed with the MDV method) includes 1,256 movers and the 1,272 firms at which they were employed.

3.2 Sample Description

In Table 2, we follow the methodology in Brav et al. (2005) and investigate whether the connectedness sample is representative of the original full sample. Panel A summarizes the representativeness of the continuous variables used in the study.[10] We first compare the overall averages and medians of each variable for the connectedness sample to the full ExecuComp sample (i.e., the universe of ExecuComp firms with valid data). We then sort the full sample into quintiles and report the quintile mean for each variable. We also report the mean and the percentage of the connectedness sample firms that fall into each quintile, based on the full sample quintile breakpoints for each variable. The reported percentages can be compared with the benchmark 20%. In Panel B, we compare the summary statistics of indicator variables for the connectedness sample and the full sample. These analyses allow us to infer whether our connectedness sample is representative of the universe of ExecuComp firms and, if so, in which dimensions.

[Table 2 about here]

The analyses show that the connectedness sample is fairly representative of the full sample, except that the connectedness sample firms are somewhat larger and executives in such firms are somewhat better paid. In unreported analysis, we compare the connectedness sample firms to the top four size quintiles of the full sample (i.e., we remove the bottom quintile of ExecuComp firms in terms of total assets). We find that controlling for firm size in this manner, the connectedness sample firms are representative in all remaining dimensions,

[10] The definitions of the variables used in our analysis are reported in the data appendix.

and thus we conclude that the difference in pay for the two samples is related to firm size. We, therefore, control for firm size in all our regression analysis.

Table 2 also provides summary statistics for both the full sample and the connectedness sample (we focus our discussion on the latter). The managers in the connectedness sample receive average compensation of $2.2 million and median compensation of $1.1 million. This implies a large positive skewness in the level of executive pay. The average (median) cash-based compensation (i.e., salary plus bonus) paid to the managers is $0.7 ($0.5) million, accounting for about 55% of total compensation, and the average (median) equity-based compensation is $1.2 ($0.3) million, accounting for 35% of total compensation. The average (median) managerial tenure is around 10 (8) years and 17% of sample managers are CEOs.

4. Empirical Results

4.1 The Economic Importance of Unobserved Firm and Manager Heterogeneities

4.1.1 Determinants of Executive Compensation

In this section, we analyze how unobserved firm and manager effects are related to compensation. We follow prior research in selecting the observable characteristics that determine the level of executive pay (see, for example, Core et al., 2008, Core et al., 1999, Murphy, 1999, and Rose and Shepard, 1997). Specifically, we regress the logarithm of total compensation on firm-level variables such as firm size, growth, stock returns, accounting returns, and return volatility, and on manager-level variables such as managerial tenure and whether the manager is a CEO. Year fixed effects are included to capture the impact of economic conditions as well as other potential year differences on pay level.[11] Our main dependent variable is log(total compensation), where total compensation is ExecuComp data item TDC1 (measured in $thousands) and is comprised of salary, bonus, other annual, total value of restricted stock granted, total value of stock options granted (using Black-Scholes), long-term incentive payouts, and all other total. Our main results and implications remain similar when we separately analyze log(salary plus bonus), log(stock plus option compensation), cash compensation as a proportion of total pay, and stock plus option compensation as a proportion of total pay as dependent variables.

[Table 3 about here]

Table 3 reports our analysis of the determinants of log(total compensation) using the *spell* method in the *full* sample. Regression (1) is a pooled OLS regression without firm or manager fixed effects. The adjusted R-squared for this regression is 49%, which is similar to the adjusted R-squared found in previous studies, such as Core et al. (1999). In regression (2), we add firm fixed effects to account for unobservable differences across firms. The adjusted R-squared in this specification increases to 66%. This indicates that unobservable firm heterogeneity (such as firm quality, firm culture about compensation practice, etc.) plays a significant role in explaining executive pay. In regression (3), we add manager fixed effects instead of firm fixed effects. The adjusted R-squared is 76%, a 27% absolute increase compared with the pooled OLS specification, and a 10% increase over the firm fixed effects specification. This suggests that unobservable managerial traits (such as leadership styles, personalities, abilities, etc.) have substantial explanatory power in determining managerial compensation. In regression (4), we control for both unobservable firm-level and manager-

[11] Executive pay could be abnormally high (due to a signing bonus, severance pay, etc.) during the years when managers join or leave a company. When we add a dummy variable which equals one for the year that a manager joined or left a company, the results are essentially the same.

level differences and the adjusted R-squared increases to 77%. Finally, in specifications (2) through (4), F tests suggest that these firm/manager fixed effects are jointly significantly different from zero.

The significant improvement in the adjusted R-square in the three-way fixed effects regression indicates that firm and manager fixed effects play an important role in explaining executive pay. Nevertheless, we note that the goal of empirical research is not to increase the R-square *per se*. Ultimately, one of our objectives is to understand the implications that the inclusion (or exclusion) of unobservable firm and managerial characteristics has on empirical executive compensation research. We explore this issue in detail in Section 4.1.3.

4.1.2 Relative Importance of Different Factors in Determining Compensation

In this section, we explore the relative economic importance of time-invariant firm and managerial heterogeneities and other factors. Such analysis requires separate identification of firm and manager fixed effects and thus we perform the AKM regression on the connectedness sample. The results reported in Panel A of Table 4 show that all the implications we obtain from the full sample regressions in Table 3 also hold for the connectedness sample.

We next use the coefficient estimates from the AKM three-way fixed effects regression (4) in Panel A of Table 4 to separate out the following components: observable time-variant firm characteristics ($W_{jt}\hat{\gamma}$), observable time-variant manager characteristics ($X_{it}\hat{\beta}$), firm fixed effects ($\hat{\varphi}_j$), manager fixed effects ($\hat{\theta}_i$), year effects ($\hat{\mu}_t$), and residuals ($\hat{\varepsilon}_{it}$).[12] We examine how much each of these components contributes to the total variation in executive pay, using

[12] The observable firm or manager characteristics are time-variant because observable time-invariant characteristics (such as a female dummy) are absorbed into the manager or firm fixed effects.

the covariance between log(compensation) and each of the components, normalized by the variance of log(compensation). Note that model R-squared is calculated as

$$
\begin{aligned}
R^2 &= \frac{\operatorname{cov}(Ln(y_{it}), Ln(\hat{y}_{it}))}{\operatorname{var}(Ln(y_{it}))} = \frac{\operatorname{cov}(Ln(y_{it}), X_{it}\hat{\beta} + W_{it}\hat{\gamma} + \hat{\varphi}_j + \hat{\theta}_t + \hat{\mu}_t)}{\operatorname{var}(Ln(y_{it}))} \\
&= \frac{\operatorname{cov}(Ln(y_{it}), X_{it}\hat{\beta})}{\operatorname{var}(Ln(y_{it}))} + \frac{\operatorname{cov}(Ln(y_{it}), W_{it}\hat{\gamma})}{\operatorname{var}(Ln(y_{it}))} + \frac{\operatorname{cov}(Ln(y_{it}), \hat{\varphi}_j)}{\operatorname{var}(Ln(y_{it}))} \\
&+ \frac{\operatorname{cov}(Ln(y_{it}), \hat{\theta}_i)}{\operatorname{var}(Ln(y_{it}))} + \frac{\operatorname{cov}(Ln(y_{it}), \hat{\mu}_t)}{\operatorname{var}(Ln(y_{it}))},
\end{aligned} \tag{5}
$$

where $Ln(y_{it})$ is the dependent variable log(total compensation). Therefore, the normalized covariance (excluding residuals) may be interpreted as a decomposition of model R-squared, with the covariance values corresponding to the fractions of the model sum of squares attributable to particular factors.[13]

[Table 4 about here]

We find that the normalized covariance of manager fixed effects, time-variant firm characteristics, firm fixed effects, and time-variant manager characteristics with log(compensation) are 0.44, 0.20, 0.04, and 0.04, respectively (Table 4, Panel B, Column (3)). Year effects and residuals each have a normalized covariance of 0.09 and 0.19. As a result, the fraction of the model sum of squares attributed to manager fixed effects is 54% (0.44/(1-0.19)), observable firm characteristics 25%, firm fixed effects 5%, and observable manager characteristics 5%. Manager fixed effects contribute the most to model R-squared, and

[13] In unreported analysis, we also follow Lemmon et al. (2008) and use analysis of variance (ANOVA) to examine the relative importance of each factor in explaining the variation in executive pay. We obtain similar implications. Specifically, in this alternative analysis we first obtain a Type III partial sum of squares for each factor, and then divide the partial sum for each factor by the total partial sum of squares over all factors for a particular model. One thing to note is that the normalized partial sum of squares should not be interpreted as the exact share of the model R-square; rather, it represents the relative power of each factor in reducing the residual sum of squares given that all the other factors have been included in the model.

observable time-variant firm characteristics are the second most important factor in explaining the variation in the level of executive pay.

In addition, the averages and standard deviations of log(compensation) and various components shown in Columns (1) and (2) of Table 4, Panel B help us interpret the economic magnitude of manager and firm fixed effects. Among all the components, manager and firm fixed effects have the largest and the second largest standard deviations and the values of the standard deviations are of an order similar to that of log(compensation). This indicates that a one standard deviation change of manager or firm fixed effects will result in roughly a one standard deviation change in log(compensation). More specifically, when manager fixed effects increase by one standard deviation of 1.13, log(compensation) changes from the average level of 7.08 to 8.21 (7.08+1.13), which can be translated into a change in total compensation from $1.2 million to $3.7 million. In other words, a one standard deviation increase in manager fixed effects will increase executive compensation by $2.5 million on average, which is economically important. Similarly, when firm fixed effects increase by one standard deviation of 0.97, log(compensation) changes from the average level of 7.08 to 8.05 and this corresponds to a change in total compensation from $1.2 million to $3.1 million.

The results presented so far indicate that time-invariant executive-specific heterogeneity is an important component and has significant incremental explanatory power beyond what is explained by extant determinants. Nevertheless, it is worth highlighting that the above analysis does not imply that observable characteristics have little power to explain executive pay variation. If the variation in observable characteristics is largely cross-sectional, including fixed effects in the regression will decrease the proportion of the variation explained by observable determinants because fixed effects will absorb the cross-sectional variation. For example, although the observable determinants have a relatively low explanatory power in the fixed effects analysis, the model that contains observable determinants alone has a high adjusted R-square of 49%. Also, the explanatory power of unobserved heterogeneities could be overstated if fixed effects absorb some cross-sectional effects from observable variables.

4.1.3 Implications for Empirical Executive Compensation Research

We first discuss the general implications of our results for empirical compensation research. As mentioned earlier, if unobservable person or firm heterogeneity is correlated with the observable characteristics, empirical methods that do not explicitly account for these unobservables could result in omitted variable bias. To further shed light on this issue, we compare the coefficient estimates in the OLS model with those in the three-way fixed effects model. We focus on the spell method results in Table 3 to facilitate the discussion (Tables 4 and 5 give similar implications). An inspection of Columns (1) and (4) in Table 3 reveals that the signs of the coefficients are similar in both specifications, but the magnitudes of the coefficients are sensitive to the specification. The average change in coefficient magnitude in the three-way fixed effects model relative to the OLS model is 50%. A Hausman test that compares the two specifications rejects the hypothesis that the OLS estimates are consistent at the 1% level. The Hausman test also rejects the hypothesis that time-invariant firm and manager heterogeneities are uncorrelated with the observable determinants.[14] Following Lemmon et al. (2008), we summarize the implication of ignoring unobserved firm and manager differences using Hsiao (2002, page 8): "Ignoring the individual effects that exist among cross-sectional units but are not captured by the included explanatory variables can lead to … inconsistent or meaningless estimates of interesting parameters."

[14] Like any specification test, the Hausman test results are suggestive. We also note that it is plausible that managerial fixed effects are correlated with observable determinants. For example, managerial fixed effects partially reflect talent, and talent may be correlated with firm size because, on average, firms grow larger when run by talented managers. Talent may also be correlated with firm performance because good managers increase firm performance.

We now discuss the specific implications of our results in the context of existing empirical evidence on executive compensation. Recent research relates the level of pay to firm size to justify an efficient contracting view that high pay is the result of optimal contracting in a competitive market for managerial talent. In the theories developed by Gabaix and Landier (2008) and Tervio (2008), better skilled managers match with larger firms. Due to the complementarity between managerial skill and firm size in production, moderately better managerial skill could lead to significantly greater profits for a large company. Consequently, compared with smaller companies, larger firms are willing to offer much higher wages. Gabaix and Landier (2008) empirically test the relation between the level of pay and firm size. Using a pooled OLS regression and the 1000 highest paid CEOs in the ExecuComp data from 1992 to 2004, they find that the coefficient of log(market value) in the equation with the dependent variable being log(total pay) is equal to 0.37 (see Table II of their paper).[15] They thus conclude that the elasticity of CEO pay to firm size is roughly 1/3.[16]

We derive similar results when using OLS regressions in our study, as Table 3 exemplifies. Log(assets), a proxy for firm size, is positively related to pay with a coefficient of 0.37 in the OLS regression. Once we include manager fixed effects, the coefficient declines significantly to 0.22. The decline (0.37-0.22) in the coefficients is significant, with a t-statistic of 11.95. The coefficient of 0.37 in the OLS model indicates that when log(assets) increases by one standard deviation of 1.76, executive pay increases by 92% ($\exp(0.37\times1.76)-1$). The three-way fixed effects coefficient of 0.22 indicates that the percentage increase in pay caused by a one standard deviation increase in firm size is 47% ($\exp(0.22\times1.76)-1$). This calculation

[15] Frydman and Saks (2010) also test the relation between compensation and firm size using historical compensation data ranging from 1936 to 2005 for the largest 50 firms. Their OLS regression gives a similar coefficient of 0.29 to 0.36 for the period from 1976 to 2005.

[16] Gabaix and Landier (2008) control for firm fixed effects (but not manager fixed effects) in one of their models and find a coefficient estimate of 0.26. However, they base their conclusions on the OLS regression results.

roughly implies that the impact of firm size on pay in the OLS model is nearly double what it is in the three-way fixed effects model. Further, the estimate of 0.22 suggests that the elasticity of CEO pay to firm size is about 1/5, lower than what is documented in the literature. Thus the takeaway is that when fixed effects are controlled, the correlation between firm size and executive pay is significantly smaller than previously documented.[17]

Next, we examine how including fixed effects aids interpretation of the pay increases associated with being CEO. The coefficient on the CEO indicator is 0.9 in the OLS model and drops to 0.3 in the manager fixed effects model. The CEO indicator potentially captures two influences on compensation: the CEO's person-specific effect (i.e., the person who becomes CEO is more skillful) and a job promotion effect (i.e., the pay increase resulting from a non-CEO being promoted to CEO). In models without manager fixed effects, the CEO indicator captures both factors. In models with manager fixed effects, the person-specific effect is absorbed into manager fixed effects and the CEO indicator captures the promotion effect only. The results suggest that, holding other variables unchanged, overall, a CEO is paid 150% (exp(0.9)-1) more than a non-CEO. For the *same* person, the pay increase due to promotion to CEO is only 35% (exp(0.3)-1).[18] Thus, the three-way fixed effects analysis allows us to isolate the promotion effect from the combined promotion plus person-specific effect.

We close this section by mentioning two major caveats to using fixed effects models. First, our analysis does not imply that every empirical specification should include firm and

[17] We alternatively use the sum of net debt and the market capitalization of equity as the proxy for firm size (as do Gabaix and Landier, 2008). This proxy is forward-looking and takes into account intangible assets. Our results are robust to this firm size variable.

[18] Note that the CEO dummy is not perfectly collinear with manager fixed effects because, in our panel dataset, a particular manager could be a non-CEO executive during some periods and a CEO in other periods. The identification of the coefficient on the CEO dummy in the presence of manager fixed effects relies on some executives being promoted from a non-CEO to a CEO or vice versa. In addition, besides using a CEO dummy to capture a promotion to CEO effect, one can include a CFO dummy, COO dummy, etc. to separate the promotion effect to these job titles from the person-specific effect. When we do this, we find that the most important of these variables by far is the CEO indicator variable.

manager fixed effects. The decision of whether or not to employ a fixed effects model depends on the goal of the research. In fact, the fixed effects approach fails if one wants to examine the direct impact of time invariant variables (such as CEO education, birth year, gender, etc.) on pay because these variables are absorbed into the fixed effects. Hence, if the explanatory variable of interest mainly varies cross-sectionally, then fixed effects could potentially wipe out the variation of interest.[19] Our fixed effects approach is more suitable when the explanatory variables of interest present sufficient time series (within manager) variation. Therefore, when employing the fixed effects model, one should interpret the results with the above limitation in mind, especially for variables of interest that mainly vary cross-sectionally and are highly time persistent.

The other caveat relates to the ability of the fixed effects model to address omitted variable bias. If omitted relevant variables or unobserved factors are time constant or at least slow moving, then the fixed effects model provides a simple and intuitive method to address the bias.[20] However, if the unobserved factors are time-changing, controlling for fixed effects is not sufficient to solve the omitted variable problem. Under this circumstance, using the fixed effects model does not help address the causality issues that researchers are often interested in; other methods (such as instrumental variables) are needed.

4.1.4 Robustness Analysis

In this section, we conduct tests to verify the robustness of the findings reported above. First, as mentioned previously, to deduce the information for non-movers, the AKM analysis depends on information about movers. When the number of movers that can be used to

[19] For example, Hermalin and Weisbach (1991) do not adopt the firm fixed effects approach in studying the effect of managerial ownership on firm value because the primary force driving the results is between-firm variation (page 107).
[20] As noted in Lemmon et al. (2008), alternative ways to address omitted variable bias, or endogeneity bias more generally, include first differencing, structural estimation, and natural experiments.

estimate fixed effects is relatively limited, the idiosyncratic component of each move may weigh heavily on the estimation and potentially increase the estimation errors of non-movers' fixed effects. The resulting noisy estimation of manager fixed effects may not be truly purged of firm-level influences, and this may exaggerate the explanatory power of person fixed effects. To address this concern, in Table 5, Panels A and B, we implement the MDV approach used in Bertrand and Schoar (2003). By restricting the sample to only managers who have moved between firms and ignoring all non-mover managers, the MDV method avoids the concern about using the information on a limited number of moving managers to back out non-movers' fixed effects.

Our main results remain intact when we apply the MDV method. As before, time invariant manager and firm heterogeneities contribute important explanatory power to the determination of executive pay and controlling for these unobserved heterogeneities mitigates potential omitted variable bias. When we decompose the variation in pay into several components using the estimates from the MDV approach, the results, reported in Panel B of Table 5, show that manager fixed effects continue to contribute the most (a share of 39%) to the model R-squared.[21] Overall, then, the main economic interpretations of the paper are the same with either the MDV method or the AKM method.[22]

The separation of firm and manager fixed effects would be more precise if one had more movers in the sample. Given the limitations of executive compensation data, we

[21] Using the AKM method, the shares contributed by manager and firm fixed effects are 54% and 5%, in comparison to shares of 39% and 19% with the MDV method. Appendix B.2 explains in detail the reasons for the differences in these numbers.

[22] Our results consistently indicate that manager fixed effects play a more significant role in explaining compensation than do firm fixed effects. The results, however, should not be interpreted as indicating firm fixed effects' unimportance. In fact, in the MDV sample, which includes movers only, firm fixed effects contribute at least 10% of R-squared (We show in Appendix B.2 that firm fixed effects play a more significant role in explaining compensation in samples with a larger proportion of movers). See Appendix B.2 and B.3 for further details.

acknowledge that the separation of firm and manger fixed effects is potentially noisy. However, it is important to emphasize that our results in Sections 4.1.1 and 4.1.3 do not depend on the separation of firm and manager fixed effects. The results from these sections imply that including both types of fixed effects is important when interpreting compensation regressions. This implication holds for the full sample, the connectedness sample, and the mobility sample, and also for the spell, MDV, and AKM methods.

[Table 5 about here]

The second robustness issue to consider is the possibility of matching. A manager may move to a company for which he is a better match, and receive a wage increase in the process.[23] Such a wage increase could result in a larger fixed effect estimate for the company that the manager matches with, although this larger fixed effect is not due to firm-specific heterogeneity in pay policy. That is, this matching possibility could contaminate our estimation of fixed effects; this problem is common to both the MDV and the AKM methods. We address this concern in two ways.

First, we note that a better match may be partially reflected in improved firm performance, which in turn leads to higher compensation. We control for firm performance in all our model specifications. Second, we examine a subsample of movers in which the matching issue is arguably less problematic. This subsample includes only the managers whose movement between firms results in a small change (within ±25%) in total compensation.[24] Although the maximum change is 25%, the mean (median) change in total compensation for this subsample of managers is small (equal to 0.78% (1.1%)). Given such a small change in total compensation, there is little if any evidence of matching in this subsample. Our results are

[23] For example, Parrino and Srinivasan (2009) find that CEOs with marketing backgrounds are more likely to be appointed by firms with larger advertising expenditures.
[24] The results are similar if we use ±10%, ±15%, and ±20% as cutoffs.

robust to this subsample analysis (reported in Table 5, Panels C and D). Including manager or firm fixed effects increases R-squared by half, and including both fixed effects increases R-squared by 70%. Also, manager fixed effects contribute the most to the model sum of squares, with a share of 68% in explaining the variation in pay. These findings continue to indicate the importance of including firm and manager fixed effects.

Despite these attempts to deal with the endogenous matching issue, we acknowledge that out efforts do not completely eliminate the matching/selection problem. In fact, the matching issue is present in some form in *any* employer-employee matched dataset (including the full ExecuComp dataset) and is not a by-product of our methodologies. In models that do not control for fixed effects, such as an OLS regression, matching can affect the coefficient estimates because matching between firms and managers could be correlated with executive pay as well as explanatory variables such as firm performance, firm size, and job tenure. If matching is only based on observable characteristics and time-*invariant* effects and does not depend on unobserved time-*variant* influences, our fixed effects approach actually provides a simple and intuitive way to address the potential matching problem that might arise when studying compensation or similar data. That is, using fixed effects controls for time-constant factors that affect managers' selecting or being selected into companies. For example, talent is a key factor that affects managers' sorting into companies and our inclusion of manager fixed effects in the model presents one way to address the selection problem associated with managerial talent. However, we note that if managers and firms are matched on the basis of not only observable characteristics and fixed effects, but also unobserved time *variant* person and firm effects, then none of the methods can fully address the matching problem.[25]

[25] Ackerberg and Botticini (2002) use the fixed effects approach to address endogenous matching in the labor market. They state that "if … unobserved characteristics are constant …, panel techniques can eliminate the

4.2 Discussion of Estimated Manager Fixed Effects

Figure 1 presents the distribution of manager fixed effects, estimated using the AKM method in the connectedness sample (i.e., regression (4) of Table 4, Panel A). Since fixed effects are estimated relative to a benchmark, the mean and the location of the estimated fixed effects may change when different benchmarks are used. However, the shape of the distribution and the standard deviation of fixed effects do not depend on benchmarks. The graph shows that the estimated manager fixed effects are roughly normally distributed, with a standard deviation of 1.12. To the extent that manager fixed effects can be interpreted as the time-invariant component of ability, this standard deviation suggests that there is a fair amount of variation in managerial ability across managers. This estimate could help parameterize models that proxy for variation in skill, such as Taylor (2010). Note that such an exercise needs to be implemented with caution because manager fixed effects could reflect the time-invariant dimension of a variety of managerial attributes, which include not only talent and ability but also risk aversion, propensity to exert effort, bargaining power, managerial entrenchment, etc.

[Figure 1 about here]

We also find that the fixed effects estimated from the AKM method and the fixed effects from the MDV method are highly correlated at 0.77 (reported in Appendix B Table A1), suggesting that manager fixed effects estimated from the two methods are similar. Compared with the graph for the AKM fixed effects in Figure 1, the distribution for the MDV fixed

endogeneity problem." They then mention that the fixed effects approach "addresses the potential 'two-sided' matching problem in our data, where unobserved principal characteristics may be correlated with observed agent characteristics and unobserved agent characteristics may be correlated with observed principal characteristics." The existing literature (Abowd et al., 1999, Bertrand and Schoar, 2003, and Goux and Maurin, 1999, among others) acknowledges that a more complicated endogenous matching problem (in which managers and firms are matched based on unobserved time *variant* effects) is a challenging issue for future research.

effects (Appendix B Figure A1) has a similar shape, but a slightly higher dispersion and fatter tails. One possible explanation is that the mobility sample is much smaller than the connectedness sample: the number of observations in the mobility sample is only one-eighth that of the connectedness sample. Greater dispersion in the MDV fixed effects could be the result of higher standard errors caused by a smaller sample.

The evidence provided thus far indicates that a significant part of the executive pay level is determined by managerial attributes that are not captured by the variables that financial researchers commonly include in their empirical analyses. We investigate what these attributes might be by hand collecting the personal characteristics of the CEOs in S&P 500 companies. These characteristics include education, gender, year of birth, and the year the executive became a CEO. We perform a cross-sectional regression of the previously estimated managerial fixed effects on these hand-collected personal traits. The regression results (Table 6) show that education is positive and significant, indicating that CEOs with more advanced degrees have higher compensation fixed effects. Because education is often used as a proxy for talent in the literature (Abowd et al., 1999, 2003), our results provide suggestive evidence that the compensation fixed effects partially reflect managerial talent.

[Table 6 about here]

Note, however, that the R-squared of regressing fixed effects on education and other personal characteristics is only 1%, thus these variables explain a very small proportion of the variation in compensation fixed effects. The rest of the variation is likely attributable to factors that are very difficult to quantify or for which the data are difficult or impossible for researchers to obtain. Such factors might include CEO power, personalities, risk attitudes, social connections, etc. In unreported analysis, we constrain the sample to CEOs and perform a pooled OLS regression similar to that in Column (1) of Table 4, Panel A, with the education variable included. Compared with the specification that excludes the education variable, the improvement in the R-squared is only 0.1%. This result is consistent with the findings in the labor economics literature that only a small part of person-specific wage components can be explained by education and other available personal characteristics (Abowd et al., 2003).[26]

4.3 Management Styles

In this section, we examine management styles and study whether different styles or traits are remunerated accordingly. Using both the AKM and MDV methods, we estimate managerial fixed effects in corporate policies, which include research and development spending (R&D), capital investment, leverage, cash holdings, and dividend payout. These managerial fixed effects in corporate policies are termed "management styles" in Bertrand and Schoar (2003). We relate manager fixed policy effects to compensation effects by estimating the following regression:

$$FE(comp)_i = \alpha + \beta \times FE(z)_i + \varepsilon_i \, , \qquad (6)$$

where i indexes managers, FE(comp) represents manager fixed effects in compensation, and FE(z) represents manager fixed effects in a particular policy variable, z. We report the β estimates in Table 7. A significant β indicates that compensation fixed effects are significantly associated with policy fixed effects. Note that Equation (6) is a cross-sectional regression because FE(comp) and FE(z) are time invariant. As a result, we interpret the estimated coefficients as correlations instead of causal relations between fixed effects. In addition, because manager fixed policy effects FE(z), as independent variables in Equation (6), are

[26] Our main specifications in Tables 3-5 do not include the education variable because educational information is sparse for non-CEO executives. Adding the education variable in the main regressions would greatly reduce the sample size. Further, the education variable is time constant and would be absorbed into fixed effects.

estimated from regressions, the β estimates are subject to classical measurement error and will be biased toward zero under standard econometric assumptions (Wooldridge, 2001).

[Table 7 about here]

Column (1) of Table 7, using the fixed effects estimated from the AKM approach, shows that compensation fixed effects are positively related to R&D, investment, leverage, and dividend payout fixed effects, and are negatively related to cash holding fixed effects. The results using the fixed effects estimated from the MDV method (column (2)) generally have similar directions but are statistically weaker, possibly due to fewer observations and less statistical power. These results suggest that high and low fixed effects in compensation correspond to differences in management styles across managers. Better paid managers invest more, both in R&D and capital investment, employ more debt, pay out more dividends, and hold less cash in the company. One interpretation is that different managers have different traits. These traits are reflected in different managerial styles and are also priced in pay. For example, managers differ in the aggressiveness of their investment and financing choices. Less risk averse or less conservative managers may invest more, use more debt, pay out more, and hold less cash, and these managers are paid more, possibly as a reward for bearing additional risk.

Finally, we examine the economic significance of the correlations between the fixed effects (Table 7, Column 3). We focus on the results from the AKM fixed effects; the MDV results have similar economic implications. For example, the difference in the compensation fixed effects between the dividend-paying companies and the non-dividend-paying companies is 0.26, which can be translated into $659 thousand of annual executive pay. This suggests that managers in the dividend-paying companies may systematically differ from those in the non-dividend-paying companies, and this difference is significantly priced in managerial pay. In addition, given a one standard deviation change in the capital investment (or R&D) fixed effects, the change in the compensation fixed effects corresponds to a change in executive pay of about $258 ($180) thousand. These numbers indicate that the correlations between compensation and policy fixed effects are economically important.

5. Conclusion

This paper examines the role of firm and manager fixed effects in explaining executive compensation and finds that the majority of the variation in executive pay can be explained by these time-invariant firm and managerial effects. The substantial heterogeneities among firms and managers could result from differences in corporate culture and in managers' latent traits, such as innate ability, personality, risk aversion, etc., none of which can be easily observed or measured. We quantify the relative importance of these firm and manager fixed effects. We also show that including firm and managerial fixed effects alters the magnitudes of the coefficients estimated for other explanatory variables. Compared to the OLS specification, the effect of firm size is notably smaller in the fixed effects specification. We also isolate the effect of being promoted to CEO from the person-specific compensation effect and find that the former is about one-third of the latter. We further relate the manager fixed compensation effects to management styles in corporate policies and find that more aggressive managers appear to be remunerated (possibly for the additional risk they bear).

We believe that accounting for firm and managerial fixed effects represents an advance in modeling the determination of executive compensation. The empirical framework in the paper provides an approach for dealing with potential omitted variable problems if omitted unobserved factors are primarily time invariant. The method we use has potentially broad applications in finance and accounting in which separately capturing firm- and manager-specific effects is desirable. This is especially important in the context of the growing attention to the role of manager-specific effects in corporate policies. For example, using the AKM method, one can examine manager and firm fixed effects in various corporate polices, such as investment, capital structure, payout, earnings management, and financial reporting, among others. One can also use the method to separately investigate mutual fund manager fixed effects and fund company fixed effects in mutual fund performance, and analyst fixed effects and brokerage firm fixed effects in earnings forecasts.

The analysis in the paper, however, is not without limitations. For example, if one is studying cross-sectional issues, then the fixed effects approach could wipe out the very variation in which one is interested. Also, the approach cannot address the omitted variable problem related to time-variant unobserved factors. Future research could investigate two exciting areas. First, allowing time variation in and interactions between firm and manager fixed effects could represent a significant step because one could then begin to address the omitted variable issue caused not only by unobserved time constant factors but also by unobserved time changing factors. Second, as new data become available, it will be interesting to see which factors (beyond those examined in this paper, which include education, birth cohort, and gender) could explain manager fixed effects. These factors could include talent, risk preferences, and personalities, among others. Clearly, these issues are very challenging but interesting to both labor and financial economists.

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Table 1
Managerial Mobility

This table provides information on the mobility of sample managers.

Panel A: Number of movers out of all managers

Mover	Number of firms in which managers have been employed	Number of managers	Percent
No	1	24,330	95.09
	Subtotal	24,330	95.09
Yes	2	1,164	4.55
	3	84	0.33
	4	7	0.03
	5	1	0.00
	Subtotal	1,256	4.91
	Total	25,586	100.00

Panel B: Number of movers in a firm

Number of movers in a firm	Number of firms	Percent	Cumulative
0	1,072	45.73	45.73
1-5	650	27.73	73.46
6-10	351	14.97	88.44
11-20	224	9.56	97.99
21-30	39	1.66	99.66
31-50	8	0.34	100.00
Total	2,344	100.00	--

Table 2

Summary Statistics and Sample Representativeness of the Connectedness Sample

This table provides summary statistics of the variables in the full sample (i.e., the universe of firms in ExecuComp) and in the connectedness sample (i.e., the sample that includes all the managers who have worked in companies that have hired at least one mover). The table also reports the representativeness of the connectedness sample, relative to the universe of ExecuComp firms. The details of the definitions and the measurement of all the variables are reported in Appendix A. For the variable *leverage*, financial (SICs 6000-6999) and utilities (SICs 4900-4999) firms are excluded because the financial structure is regulated in these industries. Panel A contains the statistics of continuous variables. In the table, we first provide the overall universe and sample averages, medians, and standard deviations. We then sort all ExecuComp firms with valid data into quintiles and report the universe averages for each quintile and the average and percentage of the connectedness sample firms that fall into each quintile, based on the universe quintile breakpoints for each variable. The reported percentages can be compared with the benchmark 20%. Because more than 20% of firms in the universe and the connectedness sample have zero equity-based compensation, we combine the first two quintiles for equity-based compensation; the sample percent for this group can be compared with a benchmark 40%. Panel B contains summary statistics for the indicator variables.

Panel A: Summary statistics and representativeness of continuous variables

Variable	Overall mean	Overall median	Overall stdev	Average and percent in each ExecuComp quintile				
				1	2	3	4	5
Total compensation$_t$ ($thousands)								
Universe	1873.19	902.28	2876.11	267.00	532.21	914.42	1673.45	5978.94
Sample	2217.79	1098.46	3188.49	272.02	535.15	917.98	1683.95	6108.61
Sample percent				15.2	17.7	20.1	22.1	25.0
Salary plus bonus$_t$ ($thousands)								
Universe	666.73	453.04	659.30	185.72	313.43	456.92	698.24	1679.35
Sample	728.52	503.55	693.82	186.95	314.48	459.07	701.13	1685.77
Sample percent				15.7	18.6	20.6	21.8	23.3
Equity-based compensation$_t$ ($thousands)								
Universe	950.45	252.69	2034.89	32.02		261.48	702.93	3723.89
Sample	1168.98	348.78	2285.71	31.67		265.28	709.05	3850.35
Sample percent				34.2		19.3	21.7	24.8
Tenure$_t$ (years)								
Universe	10.06	8.16	7.81	2.12	5.71	8.20	11.66	22.60
Sample	9.88	8	7.93	2.06	5.78	8.28	11.65	23.02
Sample percent				21.4	21.5	18.7	19.3	19.1
Leverage$_t$								
Universe	0.22	0.20	0.18	0.004	0.09	0.20	0.30	0.48
Sample	0.22	0.21	0.17	0.004	0.09	0.20	0.30	0.48
Sample percent				17.9	20.3	21.4	21.5	18.9
Assets$_{t-1}$ ($millions)								
Universe	7481.59	1230.52	21137.99	168.44	511.38	1275.42	3635.52	31817.51
Sample	9609.73	1771.80	24084.04	178.54	513.38	1294.91	3640.77	33830.42
Sample percent				14.6	17.6	20.3	22.7	24.8

Market to book$_{t-1}$								
Universe	2.01	1.48	1.48	1.00	1.20	1.49	2.04	4.32
Sample	2.04	1.51	1.47	1.01	1.20	1.49	2.05	4.27
Sample percent				18.7	19.6	20.5	20.5	20.7
Tangibility$_{t-1}$								
Universe	0.29	0.23	0.24	0.03	0.13	0.23	0.39	0.69
Sample	0.29	0.23	0.23	0.03	0.13	0.23	0.40	0.68
Sample percent				18.8	20.9	20.5	20.3	19.4
Return on assets$_t$								
Universe	0.047	0.046	0.11	-0.084	0.020	0.047	0.082	0.171
Sample	0.047	0.046	0.11	-0.082	0.020	0.047	0.083	0.171
Sample percent				20.7	19.5	20.0	19.8	19.9
Stock return$_t$								
Universe	0.19	0.12	0.52	-0.38	-0.06	0.12	0.31	0.95
Sample	0.18	0.11	0.51	-0.39	-0.06	0.12	0.32	0.93
Sample percent				20.3	20.1	19.9	19.8	19.8
Stock return volatility$_t$								
Universe	0.44	0.39	0.21	0.23	0.31	0.39	0.52	0.77
Sample	0.44	0.38	0.20	0.23	0.31	0.39	0.52	0.77
Sample percent				21.1	21.1	19.9	18.5	19.5

Panel B: Summary statistics and representativeness of indicator variables

Variable		Mean	Median	Stdev
CEO indicator$_t$	Universe	0.17	0	0.38
	Sample	0.17	0	0.38
Female indicator	Universe	0.046	0	0.21
	Sample	0.045	0	0.21
CEO chair indicator$_{t-1}$	Universe	0.66	1	0.47
	Sample	0.68	1	0.47
Dividend paying indicator$_{t-1}$	Universe	0.59	1	0.49
	Sample	0.59	1	0.49

Table 3

Determinants of the Level of Executive Compensation: Full Sample Regressions

The table presents the regression results on the determinants of executive pay, using the full universe of ExecuComp companies. The dependent variable is *log(total compensation)*. (1) is a pooled OLS regression without firm or manager fixed effects. (2) is the firm fixed effects regression, (3) is the manager fixed effects regression, and (4) is a spell fixed effects regression including both firm and manager fixed effects. The detailed definitions of all the variables are reported in Appendix A. Heteroskedasticity robust t-statistics adjusting for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1) Pooled OLS (No firm or manager fixed effects)	(2) Firm fixed effects (No manager fixed effects)	(3) Manager fixed effects (No firm fixed effects)	(4) Firm and manager fixed effects (using the spell method)
$Log(assets)_{t-1}$	0.37*** (51.29)	0.29*** (21.64)	0.22*** (23.08)	0.22*** (21.43)
Market to $book_{t-1}$	0.15*** (19.22)	0.09*** (13.43)	0.09*** (19.24)	0.09*** (18.68)
Stock $return_t$	0.20*** (19.47)	0.17*** (18.45)	0.17*** (27.95)	0.17*** (27.83)
Stock $return_{t-1}$	0.04*** (3.81)	0.08*** (10.19)	0.08*** (14.72)	0.08*** (14.28)
Return on $assets_t$	0.42*** (6.09)	0.31** (4.59)	0.38*** (7.86)	0.41*** (8.42)
Return on $assets_{t-1}$	0.31*** (4.90)	0.29*** (4.77)	0.31*** (7.35)	0.33*** (7.66)
Stock return $volatility_t$	0.91*** (15.64)	0.03 (0.42)	0.19*** (4.23)	0.12*** (2.63)
CEO chair $indicator_{t-1}$	0.08*** (4.46)	0.04*** (3.05)	0.02* (1.89)	0.02 (1.53)
$Log(tenure)_t$	0.03*** (4.41)	0.05*** (10.61)	0.04*** (7.35)	0.06*** (10.23)
CEO $indicator_t$	0.89*** (95.10)	0.87*** (99.13)	0.32*** (23.14)	0.30*** (21.26)
Female	-0.12*** (-5.70)	-0.16*** (-11.66)	N.A.	N.A.
Year effects	Yes	Yes	Yes	Yes
Adj. R-squared	0.49	0.66	0.76	0.77
P-value for F test that all fixed effects = 0	N.A.	0.00***	0.00***	0.00***
N	112,546	112,546	112,546	112,546

Table 4

Determinants of the Level of Executive Compensation: Connectedness Sample Regressions and Relative Importance of Different Factors in Determining Compensation

Panel A of the table presents the regression results on the determinants of executive pay, using the connectedness sample (i.e., the sample that includes all the managers who have worked in the companies that have hired at least one mover). The dependent variable is *log(total compensation)*. (1) is a pooled OLS regression without firm or manager fixed effects. (2) is the firm fixed effects regression, (3) is the manager fixed effects regression, and (4) is a regression including both firm and manager fixed effects. In (4), we use the AKM method to separately identify manager and firm fixed effects. The detailed definitions of all the variables are reported in Appendix A. Heteroskedasticity robust t-statistics adjusting for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively. Panel B of the table presents some statistics on the components that determine log(total compensation), using the estimation results from column (4) of Panel A. These components include observable time-variant firm characteristics ($W\hat{\gamma}$), observable time-variant manager characteristics ($X\hat{\beta}$), firm fixed effects ($\hat{\varphi}$), manager fixed effects ($\hat{\theta}$), year effects ($\hat{\mu}$), and residuals ($\hat{\varepsilon}$). The table first reports the means and standard deviations of log(compensation) and the components, and then reports the covariance between log(compensation) and each of the components, normalized by the variance of log(total compensation). The normalized covariance (excluding residuals) can be interpreted as a decomposition of model R-squared and the covariance values correspond to the percentages (in parentheses) of the model R-squared attributable to particular factors.

Panel A: Regression results using the connectedness sample

	(1) Pooled OLS (No firm or manager fixed effects)	(2) Firm fixed effects (No manager fixed effects)	(3) Manager fixed effects (No firm fixed effects)	(4) Firm and manager fixed effects (using the AKM method)
Log(assets)_{t-1}	0.37***	0.30***	0.21***	0.21***
	(41.23)	(16.46)	(18.43)	(14.88)
$\text{Market to book}_{t-1}$	0.15***	0.10***	0.10***	0.10***
	(13.46)	(11.17)	(15.81)	(15.17)
Stock return_{t}	0.20***	0.18***	0.18***	0.17***
	(14.42)	(13.75)	(20.82)	(20.30)
$\text{Stock return}_{t-1}$	0.06***	0.09***	0.08***	0.07***
	(3.80)	(7.59)	(10.64)	(9.77)
$\text{Return on assets}_{t}$	0.40***	0.20**	0.24***	0.29***
	(4.65)	(2.23)	(3.72)	(4.24)
$\text{Return on assets}_{t-1}$	0.46***	0.31***	0.33***	0.36***
	(5.45)	(3.84)	(5.60)	(5.82)
Stock return	0.91***	0.04	0.20***	0.10
volatility_{t}	(12.05)	(0.38)	(3.23)	(1.60)
CEO chair	0.09***	0.04**	0.01	0.01
indicator_{t-1}	(4.20)	(2.46)	(1.01)	(0.46)
Log(tenure)_{t}	0.03***	0.03***	0.03***	0.05***
	(3.12)	(5.77)	(4.30)	(6.81)
CEO indicator_{t}	0.92***	0.90***	0.33***	0.30***
	(78.58)	(78.60)	(18.05)	(15.76)
Female	-0.14***	-0.17***	N.A.	N.A.
	(-5.10)	(-9.09)		
Year effects	Yes	Yes	Yes	Yes
Adj. R-squared	0.49	0.64	0.73	0.75
N	65,421	65,421	65,421	65,421

Panel B: Relative importance of different components in determining compensation (using the AKM method to separately identify manager and firm fixed effects in the connectedness sample)

	(1) Mean	(2) Stdev	(3) $\dfrac{\text{cov}(\log(\textit{total compensation}), \textit{component})}{\text{var}(\log(\textit{total compensation}))}$ (Percentages of the model R-squared attributable to particular components are in parentheses)
Log(total compensation)	7.08	1.07	--
Observable time-variant firm characteristics	1.96	0.38	0.20 (25%)
Observable time-variant manager characteristics	0.16	0.13	0.04 (5%)
Firm fixed effects	0.00	0.97	0.04 (5%)
Manager fixed effects	0.00	1.12	0.44 (54%)
Year effects	0.65	0.32	0.09 (11%)
Residuals	0.00	0.47	0.19

Table 5
Robustness Tests

The table presents the robustness test results on the determinants of executive pay. The dependent variable is *log(total compensation)*. In Panels A and C, (1) is a pooled OLS regression without firm or manager fixed effects. (2) is the firm fixed effects regression, (3) is the manager fixed effects regression, and (4) is a regression including both firm and manager fixed effects. In (4), we use the MDV method to separately identify manager and firm fixed effects. Panel A presents the regression results using the mobility sample, which includes only the managers who have moved between firms. Panel B presents the relative importance of different factors in explaining compensation, using the estimation results from column (4) of Panel A. Panel C presents the regression results using the sample that includes only managers who have moved between firms with the change of total compensation within ±25% (i.e., a subsample where the firm-manager matching problem is arguably less likely). In this subsample, the mean (median) change in total compensation for managers is equal to 0.78% (1.1%). The relative importance of different factors in explaining compensation for this subsample is contained in Panel D. The details of definitions and measurements of all the variables are reported in Appendix A. Heteroskedasticity robust t-statistics adjusting for clustering within firms are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Regression results using the mobility sample

	(1) Pooled OLS	(2) Firm fixed effects	(3) Manager fixed effects	(4) Firm and manager fixed effects (using the MDV method)
Log(assets)$_{t-1}$	0.36***	0.29***	0.23***	0.29***
	(31.24)	(12.22)	(21.91)	(6.18)
Market to book$_{t-1}$	0.18***	0.10***	0.09***	0.09***
	(12.01)	(8.40)	(9.54)	(4.14)
Stock return$_t$	0.20***	0.17***	0.16***	0.17***
	(8.18)	(8.87)	(9.05)	(6.14)
Stock return$_{t-1}$	0.08***	0.10***	0.12***	0.09***
	(3.18)	(5.78)	(7.14)	(3.62)
Return on assets$_t$	0.16	-0.09	-0.07	0.08
	(0.97)	(-0.80)	(-0.64)	(0.38)
Return on assets$_{t-1}$	0.47***	0.25**	0.37***	0.38**
	(3.02)	(2.20)	(3.59)	(2.04)
Stock return volatility$_t$	0.89***	0.15	0.36***	0.25
	(8.20)	(1.25)	(4.69)	(1.45)
CEO chair indicator$_{t-1}$	0.11**	0.06**	0.05*	0.05
	(3.31)	(2.23)	(2.38)	(1.22)
Log(tenure)$_t$	0.01	0.01	0.002	0.05***
	(0.42)	(0.62)	(0.23)	(2.55)
CEO indicator$_t$	0.88***	0.75***	0.35***	0.21***
	(27.60)	(33.56)	(13.41)	(4.34)
Female	0.20	-0.20*	N.A.	N.A.
	(0.33)	(-3.72)		
Year effects	Yes	Yes	Yes	Yes
Adj. R-squared	0.46	0.63	0.65	0.71
N	8,692	8,692	8,692	8,692

Panel B: Relative importance of different components in determining compensation (using the MDV method to separately identify manager and firm fixed effects in the mobility sample)

	$\frac{\text{cov}(\log(\textit{total compensation}), \textit{component})}{\text{var}(\log(\textit{total compensation}))}$ (Percentages of the model R-squared attributable to particular components are in parentheses)
Observable time-variant firm characteristics	0.23 (29%)
Observable time-variant manager characteristics	0.03 (4%)
Firm fixed effects	0.15 (19%)
Manager fixed effects	0.31 (39%)
Year effects	0.08 (10%)
Residuals	0.20

Panel C: Regression results using the sample that includes only managers who have moved between firms with a change of compensation within ±25%

	(1) Pooled OLS	(2) Firm fixed effects	(3) Manager fixed effects	(4) Firm and manager fixed effects (using the MDV method)
Log(assets)$_{t-1}$	0.32***	0.09	0.12***	0.08
	(12.78)	(1.12)	(4.33)	(1.03)
Market to book$_{t-1}$	0.18***	0.11**	0.06**	0.09**
	(5.24)	(2.43)	(1.99)	(2.30)
Stock return$_t$	0.15***	0.09*	0.08*	0.07
	(2.91)	(1.69)	(1.72)	(1.15)
Stock return$_{t-1}$	0.07	0.08	0.09*	0.06
	(1.31)	(1.15)	(1.92)	(0.98)
Return on assets$_t$	0.18	0.13	0.16	0.34
	(0.52)	(0.36)	(0.56)	(0.93)
Return on assets$_{t-1}$	0.26	-0.03	0.13	0.06
	(0.82)	(-0.09)	(0.53)	(0.18)
Stock return volatility$_t$	0.97***	-0.48	0.07	-0.61
	(4.36)	(-1.01)	(0.36)	(-1.29)
CEO chair indicator$_{t-1}$	-0.02	-0.03	-0.05	-0.01
	(-0.34)	(-0.43)	(-1.15)	(-0.11)
Log(tenure)$_t$	0.04	0.04	0.04**	0.07
	(1.13)	(0.53)	(2.04)	(1.15)
CEO indicator$_t$	0.97***	0.48***	0.25***	0.18
	(14.19)	(3.77)	(3.37)	(1.56)
Female	-0.03	-0.02	N.A.	N.A.
	(-0.24)	(-0.06)		
Year effects	Yes	Yes	Yes	Yes
Adj. R-squared	0.50	0.75	0.76	0.85
N	1,296	1,296	1,296	1,296

Panel D: Relative importance of different components in determining compensation (using the MDV method to separately identify manager and firm fixed effects in the sample that includes only managers who have moved between firms with a change of compensation within ±25%)

	$\frac{\text{cov}(\log(\textit{total compensation}), \textit{component})}{\text{var}(\log(\textit{total compensation}))}$ (Percentages of the model R-squared attributable to particular components are in parentheses)
Observable time-variant firm characteristics	0.09 (11%)
Observable time-variant manager characteristics	0.03 (4%)
Firm fixed effects	0.03 (4%)
Manager fixed effects	0.58 (68%)
Year effects	0.12 (14%)
Residuals	0.15

Table 6
Manager Fixed Effects and Observable Managerial Characteristics

The table presents the frequency distribution of the highest degrees received by CEOs in S&P500 companies during the period from 1992 to 2008 (Panel A), and the results from regressing manager compensation fixed effects on observable time-invariant managerial characteristics (Panel B). *Education1* is equal to 1 for below bachelor, 2 for bachelors, 3 for non-MBA masters and MBAs, and 4 for doctorates. *Education2* is the number of years of education, with below bachelor being 12 years, bachelor 16 years, non-MBA masters and MBAs, 18 years, and Ph.D. 21 years. The missing degree information is imputed using the mean values of *Education1* and *Education2*, 2.74 and 17.6. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Frequency distribution of CEOs' highest degree

Education (highest degree)	Frequency	Percent	Cumulative
Below bachelor	15	1.97	1.97
Bachelor	243	31.85	33.82
Non-MBA masters	80	10.48	44.30
MBA	225	29.49	73.79
Ph.D.	102	13.37	87.16
Missing degree information	98	12.84	100.00
Total	763	100.00	--

Panel B: Results of regressing manager compensation fixed effects on CEO personal characteristics

Dependent variable = manager compensation fixed effects estimated with AKM approach on connectedness sample	(1)	(2)
Education1	0.14*** (2.63)	--
Education2	--	0.06*** (2.75)
Year of birth	-0.004 (-0.73)	-0.004 (-0.68)
Year of becoming CEO	0.004 (0.85)	0.004 (0.81)
Female	-0.05 (-0.12)	-0.05 (-0.13)
Constant	0.04 (0.00)	-0.85 (-0.09)
R-squared	0.01	0.01

Table 7

Relation between Managerial Fixed Compensation Effects and Fixed Policy Effects

The table presents the relation between manager compensation fixed effects and manager "style" fixed effects in various corporate policies. We perform regression $FE(comp)_i = \alpha + \beta \times FE(z)_i + \varepsilon_i$, where j indexes managers, FE(comp) represents manager fixed effects in compensation, and FE(z) represents manager fixed effects in a particular corporate policy variable, z. We then report the β estimates in the table, with each entry corresponding to a regression associated with one particular policy. In Column (1), fixed compensation and policy effects are estimated using the AKM method, and in Column (2), the MDV method. Column (3) reports the economic magnitude (in dollar amounts) of the Column (1) estimates. Multiplying the standard deviation of each policy variable by its corresponding β estimate in (1) gives the change in compensation fixed effects for a one standard deviation change in policy fixed effects. Based on the change in compensation fixed effects, we calculate the change in log(compensation) (i.e., log(pay2)-log(pay1)) for an executive with average pay (i.e., pay1 = sample average $2,218 thousand), holding other variables constant. We then calculate the pay change (pay2-pay1) in dollar amounts and report it in Column (3). That is, the numbers in Column (3) can be interpreted as the executive pay change given a one standard deviation change in policy fixed effects (for the dividend indicator, it is the pay difference between dividend-paying companies and non-dividend-paying companies). The details of the definitions and the measurements of these variables are reported in Appendix A. Heteroscedasticity robust t-statistics are in parentheses. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

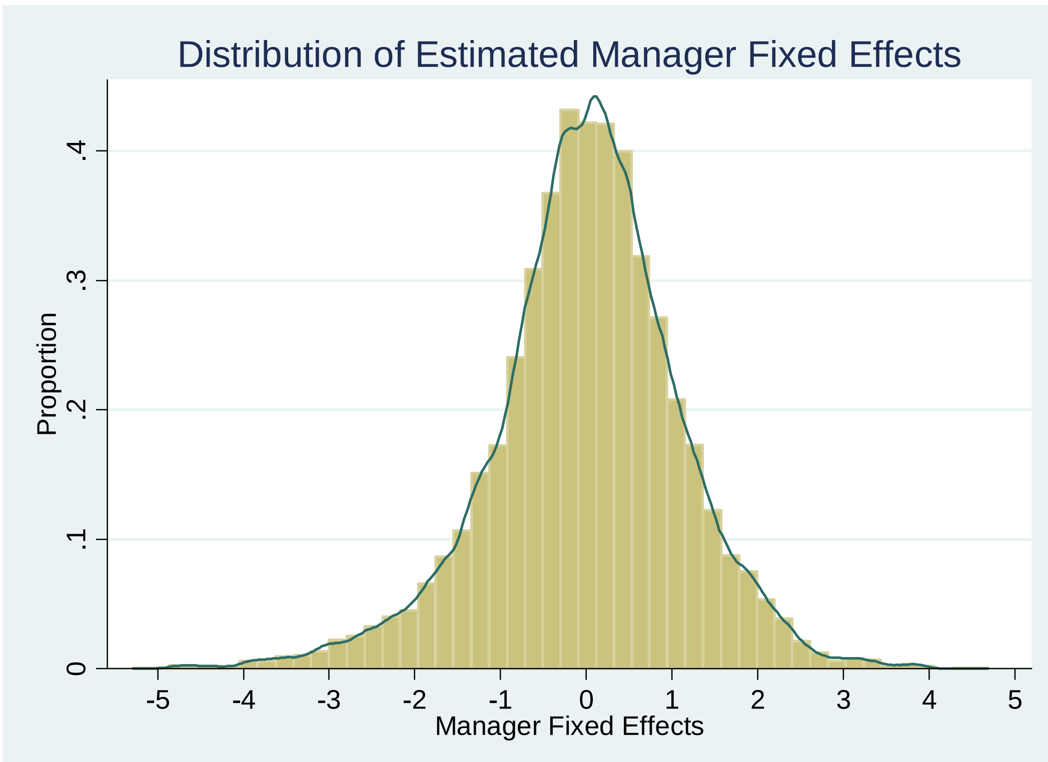
Coefficient estimates of regressing compensation fixed effects on policy fixed effects

	(1) Manager fixed effects estimated using the AKM approach	(2) Manager fixed effects estimated using the MDV approach	(3) Change in pay based on the estimates in (1) ($thousand)
R&D	1.51*** (9.15)	0.94 (1.53)	180
Investment	0.41*** (10.65)	0.25* (1.77)	258
Leverage	0.17** (2.49)	0.15 (0.58)	57
Cash holdings	-0.09*** (-3.05)	0.06 (0.53)	-66
Dividend paying indicator	0.26*** (8.89)	0.20* (1.90)	659
Dividend yield	1.66*** (3.61)	1.47 (0.84)	96

Figure 1
Distribution of Estimated Manager Fixed Effects

The figure presents the distribution of estimated manager fixed effects, using histograms and the kernel density estimation (curved line). Manager fixed effects are estimated using the AKM method in the connectedness sample (i.e., regression (4) of Table 4, Panel A). Because fixed effects are estimated relative to a benchmark, the mean and the location of the estimated fixed effects may change when different benchmarks are used. However, the shape of the distribution function and the standard deviation of fixed effects do not depend on benchmarks. In the graph, we normalize the fixed effects so that the mean value of the manager fixed effects is zero.

Distribution of manager fixed effects estimated using the AKM method in the connectedness sample



Appendix A: Definition of Variables

Variable Names	Variable Definitions and Corresponding Compustat and ExecuComp Data Items
Firm level variables	
Log(assets)	Natural log of total assets = log(data6). Assets are measured in $millions.
Market to book	(Market value of equity plus the book value of debt)/total assets = (data25*data199+data6-data60)/data6.
Tangibility	Net property, plant and equipment/total assets = data8/data6.
Stock return	Annual stock returns from CRSP.
Return on assets (ROA)	Net income before extraordinary items and discontinued operations divided by total assets = data18/lag(data6).
Return on equity (ROE)	Net income before extraordinary items and discontinued operations divided by the total book value of common equity = data18/data60.
Stock return volatility	Standard deviation of daily log returns over the past five years and then annualized by multiplying by the square root of 254.
CEO chair indicator	A dummy variable equal to one if the CEO of the company is also the board chairman, and zero otherwise.
Leverage	(Long term debt + debt in current liabilities)/total assets = (data9+data34)/data6.
Dividend paying indicator	A dummy variable equal to one if data21, common dividends, is positive, and zero otherwise.
R&D	Research and development expense/lag one year net property, plant, and equipment = data46/lag(data8).
Advertisement	Advertising expense/lag one year net property, plant, and equipment = data45/lag(data8).
Capital expenditure (Investment)	Capital expenditures/lag one year net property, plant, and equipment = data128/lag(data8).
Cash holdings	Cash and short-term investments/(total assets – cash and short-term investments) = data1/(data6-data1).
Dividend yield	Dividends per share divided by year-end stock price = data26/data24.

Manager level variables	
Log(total compensation)	Natural log of total compensation, where total compensation is ExecuComp data item TDC1 and is comprised of salary, bonus, other annual, total value of restricted stock granted, total value of stock options granted (using Black-Scholes), long-term incentive payouts, and all other total. Total compensation is measured in $thousands.
Log(salary plus bonus)	Natural log of salary plus bonus, where salary plus bonus is ExecuComp data item TOTAL_CURR. Salary plus bonus is measured in $thousands.
Log(equity-based compensation)	Natural log of total equity-based compensation, where equity-based compensation is equal to the value of options granted as valued using the Black Scholes methodology (OPTION_AWARDS_BLK_VALUE) plus the value of restricted stock grants (RSTKGRNT). Equity-based compensation is measured in $thousands.
Log(tenure)	Natural log of the number of years the manager has been with the company, which equals the difference between the year of the observation and the year when the individual joined the company.
CEO indicator	A dummy variable that equals one if the manager is the CEO in a particular year and zero if the manager is a non-CEO top executive in a particular year. This dummy variable is time variant for a given individual because a specific manager could be a CEO in some years and a non CEO in other years.
Female indicator	A dummy variable that equals one if the manager is a female, and zero otherwise.

Appendix B: Detailed Discussion of the Abowd, Kramarz, and Margolis (AKM) Method

This appendix is intended to be read jointly with "Managerial Attributes and Executive Compensation" and contains a detailed methodological and econometric discussion.

B.1 The Estimation Procedure of the AKM Method

We first start with a discussion on how to use the AKM method to obtain model estimates in the three-way fixed effects model (i.e., Equation (4) in the text):

$$Ln(y_{it})= X_{it}\,\beta + W_{jt}\,\gamma + \varphi_j + \theta_i + \mu_t + \varepsilon_{it}\,, \tag{A1}$$

where W_{jt} and X_{it} represent observable firm and manager characteristics, φ_j, θ_i, and μ_t denote firm, manager, and year fixed effects in compensation, and ε_{it} is the residual.

Including dummy variables for each manager and each firm and then estimating Equation (A1) using the standard least square dummy variable (LSDV) approach (as one does in the Mover Dummy Variable (MDV) method) is often computationally infeasible in the connectedness sample, because a large number of dummy variables associated with firms and managers require substantive computer memory.[27] In a standard two-way fixed effects model which includes firm fixed effects and time fixed effects, this problem is circumvented by using the within transformation to sweep out the heterogeneity. That is, for each cross-section, first average the two-way fixed effects equation over time to get a mean equation, and then subtract

[27] Using the standard dummy variable approach to estimate the model becomes computationally infeasible in very large datasets. To quantify this, let N be the number of observations, I the number of persons, J the number of firms, and K the number of regressors. As in Andrews et al. (2006) and Cornelissen (2008), assume that the storage of each matrix element requires 4 bytes. The total memory required in the MDV method is roughly $N\times(I+J+K-1)\times 4 + (I+J+K-1)^2\times 4$. The total memory required in the AKM method is equal to $N\times(J+K-1)\times 4 + (J+K-1)^2\times 4$, independent of the number of persons. Cornelissen (2008) further develops a memory saving Stata algorithm to reduce the memory used in the AKM method to $(J+K-1)^2\times 4$, which is independent of not only the number of persons but also the number of observations. In this paper, using AKM, we have N=65,421, I=15,352, J=1,272, and K=26 (including 16 year indicators), and the required memory is about 346MB (and only 6.7MB when using the memory saving algorithm). If the MDV approach is applied to the same dataset, the required memory is 5.5GB, which is intensive in most personal computers.

the mean equation from the original equation to obtain a transformed time-demeaned equation. Because firm fixed effects are constant within each cross-section, this transformation effectively sweeps out firm fixed effects.

In the three-way fixed effects model, because the correspondence between firms and managers is unpatterned, no transformation can simultaneously sweep out both firm and manager fixed effects. To solve the problem, the AKM method first sweeps out manager fixed effects using the within-person transformation, but keeps time and firm fixed effects, and then uses the LSDV approach to estimate variable coefficients and firm and year fixed effects. Abowd et al. (1999) note that this method results in the same solution presented in the full LSDV method. Specifically, let $Y_{it} = Ln(y_{it})$ to simplify the notation and write out the firm dummy variable: F_{jit}, which equals one if manager i works in firm j at time t, and zero otherwise. Equation (A1) can thus be rewritten as

$$Y_{it} = X_{it}\beta + W_{jt}\gamma + \sum_{j=1}^{J} F_{jit}\varphi_{\mathrm{j}} + \theta_{\mathrm{i}} + \mu_t + \varepsilon_{\mathrm{it}} \quad . \tag{A2}$$

Average Equation (A1) over $t = 1, 2, \ldots, T$ to get the cross section equation

$$\overline{Y}_i = \overline{X}_i\beta + \overline{W}_i\gamma + \sum_{j=1}^{J} \overline{F}_{ji}\varphi_{\mathrm{j}} + \theta_{\mathrm{i}} + \overline{\mu} + \overline{\varepsilon}_{\mathrm{i}} \quad . \tag{A3}$$

Subtracting (A2) from (A1) gives the time demeaned equation

$$Y_{it} - \overline{Y}_i = (X_{it} - \overline{X}_i)\beta + (W_{jt} - \overline{W}_i)\gamma + \sum_{j=1}^{J} (F_{jit} - \overline{F}_{ji})\varphi_{\mathrm{j}} + (\mu_t - \overline{\mu}) + (\varepsilon_{it} - \overline{\varepsilon}_{\mathrm{i}}) \quad . \tag{A4}$$

Manager fixed effects θ_i are thus swept out and Equation (A4) can be estimated using the LSDV method. Based on Andrews et al. (2006), Hsiao (2002), and Wooldridge (2001), the manager fixed effects can later be recovered using the following equation ($\overline{\mu}$, often treated as the benchmark in estimating time effects, is assumed to be zero):

$$\hat{\theta}_{\mathrm{i}} = \overline{Y}_i - \overline{X}_i\hat{\beta} - \overline{W}_i\hat{\gamma} - \sum_{j=1}^{J}\overline{F}_{ji}\hat{\varphi}_{\mathrm{j}} \quad . \tag{A5}$$

Interested readers can follow the above steps to apply the AKM method.[28] Intuitively, using the pay differential of a manager who has worked in different companies, we can determine the fixed effects for all the firms at which he or she has been employed (with one firm fixed effect being the benchmark). Once the firm fixed effects are identified, the personal fixed effects can be determined by subtracting the observable determinants and firm fixed effects from the pay earned by the manager.

B.2 The Econometric Properties of the Spell, MDV, and AKM Estimates

In addition to the AKM method, the paper shows that we can estimate Equation (A1) using the more traditional spell fixed effects and the MDV methods. Here we discuss the econometric properties of the model estimates using the three methods.

Recall that the spell method rewrites Equation (A1) as $Ln(y_{it}) = X_{it}\,\beta + W_{jt}\,\gamma + V_s + \mu_t + \varepsilon_{it}$, where V_s, equal to $\varphi_j + \theta_i$, is a dummy variable representing each unique combination of manager i and firm j. According to Abowd et al. (1999) and Wooldridge (2001), the estimates of β and γ from the spell method are consistent and unbiased if the error term is uncorrelated with all the right-hand-side variables (formally, $E(\varepsilon_{it}|X_{it}, W_{jt}, V_{s,}, \mu_t)=0$). The spell estimator is also efficient when the random error ε is homoscedastic and serially uncorrelated.

As with the spell estimator, the parameter estimates from the MDV method are consistent and unbiased under the standard econometric assumption of $E(\varepsilon_{it}|X_{it}, W_{jt}, \theta_i, \varphi_j, \mu_t)=0$, and efficient with homoscedastic and serially uncorrelated random errors. The estimates of the

[28] For more information, refer to Abowd et al. (1999) and Abowd et al. (2002) for detailed discussions on the estimation method, and to Andrew et al. (2007) and Cornelissen (2008) for the algorithm developed using Stata.

fixed effects θ_i and φ_j are best linear unbiased, i.e., unbiased and efficient among all linear estimators. However, as Hsiao (2002) and Wooldridge (2001) note, the estimates of the fixed effects are not consistent. The main intuition as follows: each time a new cross-section of observations is added, another fixed effect (φ_j or θ_i) is added, and information does not accumulate fast enough on the fixed effects when the number of cross sections goes to infinity. Although Hsiao (2002) notes that the estimates of fixed effects are consistent if and only if the number of time periods goes to infinity, this condition is rarely satisfied because, in panel data, the number of time periods is usually limited.

The econometric properties of the AKM estimates of β and γ are the same as the spell and the MDV methods. The properties of the estimates of the fixed effects θ_i and φ_j are the same as those of the MDV method, that is, unbiased and efficient but inconsistent. Also, as discussed in Section 2.2.3 of the paper, both the MDV and the AKM methods are subject to a potential limited mobility bias.

Our estimation results find that manager fixed effects estimated from the AKM and the MDV methods are close, with a correlation of 0.77 (Appendix B Table A1) and similar distributions (Appendix B Figure A1). We then discuss two additional econometric properties of the AKM method, in the context of comparing AKM with MDV. First, the β and γ estimates are more precise using the AKM method due to the larger connectedness sample (relative to the smaller mobility sample used in the MDV method). In our application using ExecuComp data, the mobility sample includes 8,692 observations, 1,256 managers, and 1,272 firms, while the connectedness sample includes 65,421 observations, 15,352 managers, and 1,272 firms. Through group connection, the AKM approach increases the sample size about tenfold, and the resulting coefficient estimates are more precise because standard errors are proportional to

$1/N^{0.5}$, where N is the sample size. For example, the standard errors of the AKM estimates (Table 4 of the main paper) are about 1/3 of those of the MDV estimates (Table 5).[29]

Second, using the AKM method, the model explanatory power attributable to firm and manager fixed effects is 5% and 54% (Table 4, Panel B), while the shares are 19% and 39% using the MDV method (Table 5, Panel B). The differences in the percentages between the two methods are the result of sample difference and normalization procedure, as described next.

If we apply the AKM method to the mobility sample, firm and manager fixed effects respectively explain 11% and 45% of the model R-squared. The improvement (from 5% to 11%) of the relative importance of firm fixed effects is due to the fact that the mobility sample includes only movers while the connectedness sample includes movers and non-movers. For each individual mover manager, firm fixed effects contribute to his or her pay variation because the manager switches between companies that often have different firm fixed effects. In contrast, for the non-mover managers in the *same* company, firm fixed effects do not contribute to the pay variation between these managers because they have the same firm fixed effects. Firm fixed effects contribute to the pay variation of the non-mover managers who belong to different firms. That is, firm fixed effects contribute to the between-firm (but not within-firm) pay variation, and possibly play a more important role in explaining compensation for mover managers than for non-mover managers. This indicates that in a sample with a larger proportion of movers (such as the mobility sample), firm fixed effects may play a more significant role in explaining compensation.

[29] Note that the increased precision applies to the coefficient estimates (β and γ) of the observable explanatory variables in the model, and may not apply to the estimates of the fixed effects. For the estimates of the fixed effects, the caveat is that while the extra observations add power, it is still the case that identifying the non-mover fixed effects ultimately hinges on the movers, who only make up a small proportion of our sample.

Using the AKM method on the mobility sample, the results are closer to but not the same as those attained from the MDV method (Table 5, Panel B) (11% and 45% vs. 19% and 39%). The remaining discrepancy is due to the AKM normalization procedure. The AKM method normalizes the fixed effects so that they are comparable across different groups (details in Appendix B.3). In contrast, the MDV method does not normalize the fixed effects. When we normalize the MDV fixed effects using the AKM normalization procedure, the firm and manager fixed effects respectively contribute 11% and 45% of the R-squared, identical to the results from applying the AKM method to the mobility sample.

B.3 The AKM Normalization Procedure

A practical estimation issue in the AKM method is normalization. Abowd et al. (1999) show that within each group, all person and firm effects are identified up to a scale. Specifically, suppose there are J firms and I managers in one group. Then J+I-1 firm and manager effects will be identified in this group because one firm or manager effect must be taken as the benchmark: the other J+I-1 fixed effects are expressed as differences from the reference fixed effect in the group. Overall, exactly M + N − G total person and firm effects are identified, where M, N, and G are the total number of persons, firms, and groups in the sample.

Because manager and firm fixed effects are identified relative to a benchmark within each group, and each group has its own benchmark, the estimated firm and manager effects are directly comparable only within the same group, not across groups. We follow the normalization procedure suggested by Cornelissen (2008) to ensure that the fixed effects across groups can be compared.[30] This procedure first normalizes the mean firm fixed effects for each group to zero and adds the group mean firm fixed effect to manager fixed effects (to ensure that Equation (A1) holds). The procedure then subtracts the grand mean of manager fixed effects from each manager fixed effect and adds this grand mean manager fixed effect to the intercept.

Although the normalization procedure provides one way to make fixed effects "comparable" across groups, it could change the relative explanatory power of firm and manager fixed effects. Because different groups have different benchmarks (which are mean firm fixed effects for each group, as discussed above), normalization will affect the relative location and variation of the fixed effects across groups. That is, the between-group explanatory power will be re-weighted between firm and manager fixed effects after normalization. Within a group, the fixed effects have one common benchmark and normalization will not change the relative location or variation of fixed effects and thus should not affect the explanatory power of firm and manager fixed effects.

To check the robustness of our results with respect to the normalization procedure, we re-estimate all our regressions using only the largest group (so normalization is not necessary), which is composed of around 65% of the connectedness sample; we find similar qualitative results (available upon request). We also re-examine the relative importance of different factors in determining compensation using only the largest group in the sample. The AKM results from the largest group in the connectedness sample show that firm and manager fixed effects contribute 3% and 56% of the R-squared (Column 1 of Appendix B Table A2). The MDV results from the largest group (70% of the full mobility sample) in the mobility sample show

[30] In contrast, the MDV method does not normalize the fixed effects and each group has its own benchmark (and these benchmarks are typically the dummy variables automatically dropped by statistical software). As a result, the MDV fixed effects are not comparable across groups.

that firm and manager fixed effects contribute 10% and 47% of the R-squared (Column 2 of Appendix B Table A2). As in the main text, these results consistently suggest that manager fixed effects play a more significant role in explaining executive compensation than do firm fixed effects.

Table A1

Statistics on Manager Fixed Effects Estimated Using the AKM and MDV Methods

The table presents the statistics on manager fixed effects estimated using the AKM and MDV methods. Because the MDV method is only applied to movers and the AKM method can be applied in a larger sample, to ensure that the analyses in the table are implementable and the statistics comparable, we base the analyses on movers only. That is, we obtain the manager fixed effects using the two methods, match their fixed effects by executive ids, and then keep only movers' fixed effects in the analysis. Because fixed effects are estimated relative to a benchmark, the mean and the location of the estimated fixed effects may change when different benchmarks are used. The shape of the distribution function, the standard deviation, and the correlations of fixed effects, however, do not depend on benchmarks. In Panel A, we normalize the fixed effects so that the mean value of the manager fixed effects is zero. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Summary statistics of the manager fixed effects estimated using the AKM and MDV methods

Variable name	Mean	Stdev	P10	P25	P50	P75	P90
Manager fixed effects estimated using the AKM method	0.00	1.02	-1.19	-0.58	-0.001	0.66	1.26
Manager fixed effects estimated using the MDV method	0.00	1.21	-1.49	-0.72	0.01	0.78	1.43

Panel B: Correlation between the manager fixed effects estimated using the AKM and MDV methods

Correlation	Manager fixed effects estimated using the MDV method
Manager fixed effects estimated using the AKM method	0.77***

Table A2

Relative Importance of Different Components in Determining Compensation (Based on the Largest Group)

The table presents the relative importance of different factors in explaining compensation, using the estimation results from the largest groups in the data samples. Column (1) presents the AKM results from the largest group (65% of the full connectedness sample) in the connectedness sample and Column (2) presents the MDV results from the largest group (70% of the full mobility sample) in the mobility sample. Detailed information on how to estimate the relative importance is contained in Table 4 of the paper.

	$\frac{\text{cov}(\log(\textit{total compensation}), \textit{component})}{\text{var}(\log(\textit{total compensation}))}$ (Percentages of the model R-squared attributable to particular components are in parentheses)	
	(1) Largest group in the connectedness sample	(2) Largest group in the mobility sample
Observable time-variant firm characteristics	0.20 (25%)	0.23(29%)
Observable time-variant manager characteristics	0.04 (5%)	0.03(4%)
Firm fixed effects	0.02 (3%)	0.08(10%)
Manager fixed effects	0.45 (56%)	0.37(47%)
Year effects	0.09 (11%)	0.08 (10%)
Residuals	0.20	0.21

Figure A1

Distribution of Estimated Manager Fixed Effects

The figure presents the distribution of estimated manager fixed effects, using histograms and kernel density estimation (curved line). Manager fixed effects are estimated using the MDV method in the mobility sample (i.e., regression (4) of Table 5, Panel A). Because fixed effects are estimated relative to a benchmark, the mean and location of the estimated fixed effects may change when different benchmarks are used. However, the shape of the distribution function and the standard deviation of fixed effects do not depend on benchmarks. In the graph, we normalize the fixed effects so that the mean value of the manager fixed effects is zero.

Distribution of manager fixed effects estimated using the MDV method in the mobility sample