The Market for CEO Talent: Implications for CEO Compensation[1]

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We study the market for CEO talent in public US corporations from 1993-2005. We find large fragmentation of CEO talent pools. In particular, about 68% of new CEOs are former employees of their own firm ("insider CEOs"), and 86% are former employees in firms belonging to the same industry (including insider CEOs). Talent pool structure explains several compensation practices: CEO compensation is only benchmarked against other firms, and pay-for-luck is prevalent only when the industry has a small percentage of insider CEOs. Finally, we study the importance of talent pools within the Gabaix-Landier (2008) size-proxying-for-talent framework, for which we find little support when incorporating the fragmentation of CEO talent pools. In light of this evidence, we offer a reinterpretation of the Gabaix-Landier results.

[1] We thank Eric Talley and participants at the Conference for Empirical Legal Studies at Cornell (2008) for valuable feedback. All errors are our own.

1. Introduction

Over the last several decades scholars have been debating the forces that determine executive compensation. On the one hand, many theorists put a strong emphasis on the substitutability of CEO talent in the economy (Rosen, 1992, Murphy and Zabojnik 2007, Gabaix and Landier 2008, Himmelberg and Hubbard 2000, Hubbard 2005). On the other hand, others assume that CEO talent is quite hard to substitute, because of e.g. managers having unique firm-specific knowledge or a style that is hard to replicate (Bertrand and Schoar 2003), or because of other frictions such as asymmetric information (Fama 1980) or managerial entrenchment (Jensen 1986, 1993).

How homogenous is the market for CEO talent? Understanding the level of heterogeneity of managerial talent pools has far-reaching implications for interpreting executive compensation. To the extent that the market for corporate talent is homogenous, CEOs and firms meet in this market for corporate talent, such that CEO compensation in equilibrium would reflect the demand and supply for their services (Gabaix and Landier 2008). However, if talent is largely firm-specific, then both managers and firms would have very few outside opportunities to choose from, and compensation would be shaped by the bargaining position that each party has in the negotiation process (Jensen 1993, Bebchuk and Fried 2003).[2]

In this study, we shed light on the level of heterogeneity in managerial talent pools across firms and the relation between CEO talent pool structure and executive compensation. Overall, we find large heterogeneity in managerial talent pools, and a significant number of industries in which CEOs are chosen mostly from within their own firm. We find strong evidence that talent

[2] Talent pools could be the result of several reasons such as unique CEO skills that are acquired only through experience in the firm, asymmetric information about potential candidates from outside the firm, entrenchment of insider managers and others. We do not distinguish among these frictions. We only assume that firms face large costs if they attempt to choose CEO candidates from outside the pool and that CEO candidates are unlikely to find opportunities as CEOs outside the talent pool, and treat the talent pools themselves as exogenous.

pools affect compensation practices. Industries in which talent pool is largely firm-specific do not benchmark their CEO compensation against other firms in the industry-size group, and they do not pay their CEO for industry-wide performance ("pay-for-luck"). In contrast, benchmarking is prevalent in industries in which CEO positions are likely to be filled by managers from other firms in the industry ("outsider CEOs"). Our results complement the results of Murphy and Zabojnik (2007), who document that CEO compensation is higher for outside CEOs and in industries with more outside CEOs. They also add to the results of Himmelberg and Hubbard (2000) and Hubbard (2005), who use size rather than the percentage of outsiders as a proxy for the inelasticity of the supply of CEOs.

Our first step is to identify the pools for CEO talent across different industries. Toward that end, we collect information from 1,827 CEO replacements in S&P 1500 companies between the years 1993 and 2005. For each new CEO, we identify her position before becoming CEO, as well as the firm and the industry from which she arrived. From these revealed choices of firms and new managers, we draw inferences regarding the talent pools from which CEOs in different companies and industries are chosen.

We find that, in general, managerial talent pools are quite industry-specific and often even firm-specific. Prior experience in managing production is one of the fundamental skills that new CEOs often have. Using 10 industry group and excluding interim CEOs[3], 86% of the new CEOs come from the same industry sector, split between lower-level managers of the same company (*68%)* and managers from other companies within that same industry (*18%)*. Interestingly, we find little variation in these attributes over time. For example, 86% of the new managers come from the same industry in 1993-1995 compared to 87% in 2003-2005.

Next, we study the relation between CEO talent pools and CEO compensation. First, we consider the relation between talent pools and the practice of benchmarking compensation. A

[3] We find that 7% of the 1,827 new CEOs are interim CEOs.

common practice by many boards of directors is to use peer groups from similar industry and size as a benchmark for CEO compensation. Bizjak, Lemmon, and Naveen (2008) find widespread evidence for benchmarking, and conclude that the practice is consistent with competitive CEO labor markets, rather than with opportunistic board behavior that does not tie pay to performance.

We argue that benchmarking should be more prevalent in industries in which talent is not firm-specific, since in those cases, compensation in other firms better reflects the outside opportunities of firms and managers (Holmstrom and Kaplan 2003). However, in industries in which talent is firm-specific, benchmarking would seem less compellingly due to competition for CEO talent. If benchmarking is primarily a way for CEOs to receive more compensation independent of performance, we would expect no relationship between talent pool structure and benchmarking.

Consistent with labor market considerations driving the practice, we find strong evidence that benchmarking is prevalent *primarily* in industries in which new CEOs tend to come from outside the firm. In contrast, for firms in industries in which CEO talent pools are almost entirely firm-specific, the relative compensation in the industry has little effect on compensation decisions inside the firms. This result suggests that the observed benchmarking practices across industries seem consistent with competitive CEO labor markets.

Second, we study the relevance of industry-wide shocks to CEO compensation. Previous studies have shown that firms tend to tie CEO compensation not only to firm-specific performance but also to performance of the industry and the economy (e.g., Bertrand and Mullainathan 2001). This "pay-for-luck" was interpreted as a bad compensation practice by some scholars (e.g., Bertrand and Mullainathan 2001, Bebchuk and Fried 2003), while others have raised the possibility that the correlation is due to a correlation between industry conditions and supply and demand for CEO talent (Himmelberg and Hubbard 2000, 2005). We find evidence that pay for luck is due to changes in the supply and demand for CEO talent, as it only seems to occur in industries with the largest percentage of outsider CEOs. We find that firms in industries in which CEO talent is largely firm-specific do not tie executive compensation to industry-wide performance.

Third, we study the importance of firm size as a proxy for the relative talent of different CEOs. Gabaix and Landier (2008, henceforth GL) present a model in which more talented CEOs are attracted to larger firms, predicting that changes in CEO compensation should depend both on changes in the size of the firm in which the CEO operates and the changes in the size distribution of firms in the economy (capturing the productivity of talent across firms, and hence the outside opportunities of CEOs with different talents). Their specification assumes that CEO skills are substitutable across firms, and that profitability is a function of skills and firm size. Therefore, in equilibrium, more talented CEOs will be attracted to larger firms. Given our findings of the importance of heterogeneous firm- and industry-specific skills, we explore whether the size distribution of firms in the industry (the relevant measure of productivity of talent for the specific CEO), better explains variation in compensation than size distribution of all firms in the economy.

We find that despite the clear evidence of fragmentary CEO talent pools, variations in firm size (as a proxy for talent a-la GL) within industries explain only a very small portion of the variation in CEO compensation over time. We explore several reasons for this finding and report results suggesting that the ‘size of the reference firm’ in GL might capture market-wide CEO pay-inflation of all firms in the economy not directly related to the distribution of firm size in the economy. Specifically, the average CEO compensation for a *constant-size* group across time drives out the importance of the reference firm size in explaining CEO compensation. Exploring this economy-wide pay-inflation is left for future research.

The rest of the paper continues as follows. In section 2, we describe our data collection process and the construction of the main variables. Section 3 provides the analysis of the benchmarking results. Section 4 provides the analysis of pay-for–luck. In section 5, we revisit the Gabaix and Landier (2008) framework and section 6 concludes.

2. Data and variables

We study the market for CEO talent by identifying the background of new CEOs in the largest public U.S. corporations. Our universe of firms includes all firms in the Execucomp database for the years 1993-2005. Execucomp provides information on the five highest paid top executives for firms included in the S&P 1500 composite index (or that have belonged to it in the past). Our sample starts in 1993, as Execucomp started a full collection of the data then. The database consists of 24,084 firm-year observations.

2.1 Identifying new CEOs

We first identify entry of new CEOs in the sample. Table 1 shows the identification procedure. For some firms in the database, Execucomp identifies the executive who is the CEO (variable *annceo*), and the year in which the CEO was appointed or reappointed (variables *becamece* and *rejoin*, respectively). For firms for which these three variables are available, we define a 'new CEO' as a CEO whose year of becoming a CEO or of rejoining the firm is the same as the recorded firm-year. This procedure allows us to identify whether a CEO is new in a total of 21,339 firm years.

For firms with missing data on *becamece* and *rejoin* but where *annceo* is not missing, we look at whether the same executive was identified by Execucomp as a CEO in the previous year. If a different executive was the CEO then we define the current CEO as a new CEO. If the variable *annceo* is also missing or if the firm is not in the database in the previous year, then we read the proxy statement in that year and in the previous year to identify whether the CEO is new. This procedure allows us to identify whether the CEO is a new CEO in additional 2,064 firm-years. Our final sample therefore consists of 23,403 firm-years or 97% of the entire Execucomp database. Of the 23,403 firm years we identify 1,890 firm years in which the CEO was new.[4]

2.2 Identifying CEO Background

Securities regulation section 229.401 requires that firms provide background information in their proxy filings about each executive officer and director. This information includes each person's principal occupations and employment during the past five years; the name and principal business of any corporation or other organization in which such occupations and employment were carried out; and whether such corporation or organization is a parent, subsidiary or other affiliate of the firm.

We read the background information for each new CEO from the proxy statements and identify the name of the previous employer of the CEO and the occupation of the CEO under that employer. We were able to find proxy statement information for 1,827 out of the 1,890 new CEOs (about 97%).

In some cases, new CEOs are entering the firm few months before becoming CEOs, to ensure a smooth transition with the current CEO. We argue that the last employer of these new CEOs (i.e., before becoming CEO) should not be the current firm, since the decision to have them as CEOs was most probably made before they entered the current firm. Instead, if the CEO was affiliated with the current firm for less than two years, we use the previous employer and position of the CEO as the new CEO’s last position before becoming CEO. In other cases, boards

[4] For 3% of firm-years, we could not identify whether the CEO was a new CEO in the particular year for various reasons, such as the firm does not identify who the CEO is, or the firm has more than one CEO or the firm does not have electronic filings in that particular year to corroborate that the CEO is new.

choose interim CEOs while looking for a new, non-interim CEO. We define a CEO as an interim CEO if the firm explicitly writes in the proxy statement that the CEO is an interim CEO, or if the CEO is replaced within a year of becoming a CEO.

Next, we identify the four-digit SIC industry code of the new CEOs' previous employer. If the previous employer was a public firm, the industry code is taken from the CRSP header file. If the employer is a private firm, the code is taken from the Hoovers' database. In the few cases where the information is not available in CRSP or in the Hoover database, we assign an industry code based on the SIC code description and the information collected about the previous employer.

Table 2 presents summary statistics of our sample. Panel A shows that out of the 1,827 new CEOs between 1993 - 2005, 1,147 (63%) are insiders, whose prior employer was the firm for at least 2 years. An additional 547 new CEOs (30%) are outsiders, i.e. they did not work for at least 2 years at the firm before becoming CEOs. An additional 133 new CEOs are interim CEOs (7%). From the 547 outsiders in the sample, a total of 312 CEOs come from a firm that belongs to the same industry.[5] Therefore, a total of 1,459 CEOs come from either inside the firm or from a firm in the same industry, which is 86% of all non-interim CEOs.

Panel A also shows that these characteristics are relatively stable over the years. Between 1993-1996, 63% of the new CEOs were insiders, 31% were outsiders, and 57% of the outsiders came from within the industry, compared with 60%, 32%, and 59% in the years 2003-2005.

These numbers are consistent with the numbers in Murphy and Zabojnik (2007), who find an average of 32.7% of new hires between 2000-2005 are outside hires. For the years 1990-2000 they find an average of 27% of CEOs who are outside hires, but their sample for that period

[5] Our industry definitions follow those on Kenneth French's website, using the 10 industry group classification here (in the later sections we primarily use the 48 industry groups). Using 48 industry groups, the number of managers who come from the same industry is 215.

includes only Forbes 500 firms, which are larger firms than the firms in our study and larger firms tend to hire fewer outsider CEOs.

Table 2 panel B shows the distribution of prior occupation of outsider CEOs. Out of the 547 outsider CEOs, 32% were already CEOs in other companies before joining the firm, out of which 19% were CEOs in public companies. However, the majority of new outsider CEOs (68%) were not CEOs in their previous employment, although many of them came from public corporations (48%).

Prior occupations of outside CEOs have changed somewhat over the years. There are slightly more former CEOs in recent years than in previous years (36% in 2003-2005 vs. 30% in 1993-1995). This increase seems driven by an increase in hires of former CEOs from the private sector (18% in 2003-2005 versus 13% in 1993-2005).

Table 2 panel C shows the distribution of prior occupation of insider CEOs. The table is based on the subsample of the 599 insider CEOs for which we collect this information.[6] The most common prior occupation of the insider CEOs is Chief Operating Officer (39%), followed by division manager / Vice president (23%) and company President (20%). These three positions are mainly operational, and involve managing the day-to-day operations of the company. Only 4% of the insiders were Chief Financial Officers, suggesting that skills in the financial aspects of the corporation might be less important for new CEOs than skills in the operational aspects of the corporation. Finally, there hasn't been much change in prior occupation of new insider CEOs over the years.

2.3 CEOs and Industry pools

Since CEOs are coming mostly from within the corporation and outsider CEOs are typically from the same industry group, experience in the firm and in the industry in which the

[6] We gather the information from proxy filings.

firm operates are significant determinants of CEO hiring. In this section, we take a closer look at the industry experience of new CEOs. We count the number of new CEOs from each of the 10 industry groups from which they come from, and measure what fraction of these accepted a CEO position in each of the 10 industry groups. The end-result is a 10 by 10 matrix (see Table 3), where each row represents an industry from which CEOs come and each column represents an industry to which CEOs go. In each cell (i,j) we calculate the fraction of CEOs coming from industry i and going to work in industry j over the whole sample.

The first two columns in Table 3 are the number of insider and outsider CEOs for each of the 10 industry groups. There is a large variation in the percentage of insiders across industries. The industry with the fewest insider CEOs is the high-tech industry, where only 55% of the new CEOs are insiders. The industry with the largest number of insider CEOs is the energy sector, where 83% of the CEOs are firm insiders.

The next 10 columns show the migrations of outsider CEOs across different industry groups. For example, the first row shows that out of the 28 new CEOs in the industry which manufactures nondurable goods, 18 (64%) came from that same industry, 3 (11%) came from the manufacturing industry, one (4%) came from the wholesale and retail industry and 6 (21%) came from the ‘Other’ industry.

Likewise, there is a large variation across industries in the talent pools from which companies choose new CEOs. For example, firms in the high-tech industry choose new CEOs from almost all industries. In contrast, firms in the health sector choose CEOs from only 4 industry groups.

The table also summarizes the portion of new CEOs coming from a certain industry group ending up in another group. For example, column 1 shows that out of the 37 candidates who had experience in the nondurable good industry, 18 (47%) became new CEOs in the nondurable good industry, one (3%) became a CEO in the durable good industry, 7 (19%)

became CEOs in the manufacturing industry, 6 (16%) became CEOs in the high-tech industry, etc. To illustrate the large variation in the distributions, CEOs in the manufacturing industry come from 9 different industries whereas CEOs in the energy industry come from only two industries.

Our classification of industries might be too coarse, and therefore might miss some variations in outsider CEO hires within classified industry groups. We therefore also consider the distribution of outsider and insider new CEOs across a finer classification of 48 industry groups in panel B of Table 3. Among industries that have 10 or more replacements in the database, the industries that have the largest percentage of insiders are Construction (92%), Steel Works (85%), and Transportation (82%). Among the industries that have the smallest percentage of insiders are Trading (41%), Aircraft (47%), Computers (51%) and Personal Services (53%).

3. Benchmarking

Our goal is to study the extent to which variations in talent pools explain cross-sectional variation in CEO compensation. We conduct three tests of the effects of the talent pool structure on the structure of CEO compensation. The first test measures the extent of benchmarking CEO compensation (this section), the second explores the importance of 'pay-for-luck' or pay for industry-wide performance (section 4), and the last considers the relation between firm size and compensation as in GL (section 5).

In determining CEO compensation, public corporations as well as compensation advisors rely on compensation to CEOs in other, similar firms. This practice, called benchmarking, is perhaps the most convenient way to ensure that CEO compensation is adjusted for changes in the supply and demand forces in the economy for CEO talent and to establish a CEO's reservation wage (Holmstrom and Kaplan 2003). On the other hand, benchmarking opponents have been worried that benchmarking may lead to CEO compensation increases regardless of performance.

Bizjak, Lemmon, and Naveen (2008, henceforth BLN) find widespread evidence of benchmarking CEO compensation to that of other firms, but no systematic evidence that the use of benchmarking is more prevalent in firms with weaker governance. They also find that benchmarking is more likely for executives with shorter tenure and with better firm performance. BLN also consider labor market effects through proxies such as firm age and the unemployment rate, but do not consider direct evidence from CEO talent pools as this paper.

CEO talent pools could have a significant effect on benchmarking. In industries with a large fraction of outsider CEOs, the CEO's outside option should be determined by the compensation of CEOs in other firms, most likely in the same industry. In a competitive labor market, firms would adjust the compensation of the CEO to that of others in the industry (Oyer 2004). If, however, there are very few outsider CEOs in the industry and the relevant talent pool of CEO candidates is given by top executives from inside the firm, then CEO compensation in other firms should not be an important determinant of the compensation to the manager. In those industries, any evidence for benchmarking could rather be interpreted as evidence for opportunistic pay-setting practices, or CEOs being compensated without regard to changes in their outside opportunities.

3.1 Benchmarking Methodology

A natural way to examine whether CEO compensation is benchmarked against peer groups is to test whether changes in CEO compensation between year t-1 and year t are explained by the relative position of the CEO compensation in year t-1 vis-à-vis compensation in the peer group (the benchmark), after controlling for the relevant variables that determine compensation. In particular, we closely follow the procedure in BLN, whose specification is as follows:

$$\Delta Compensation_{i,t} = a_1 * Distance(Compensation_{i,t-1}, Benchmark\ Compensation_{t-1}) + a_2 * Controls_{it} + Error_{it}. \quad (1)$$

The function Distance(Compensation $_{i,t-1}$, Benchmark Compensation $_{t-1}$) is a measure of the distance between CEO compensation in year t-1 and the benchmark compensation in the same year. Like BLN, we consider the benchmark compensation as the median compensation in the peer group in the previous year and employ two different proxies for such distance. First, a Low Compensation Dummy that equals one if compensation$_{i,t-1}$ < benchmark median compensation$_{t-1}$ and zero otherwise. Second, the cumulative distribution function of the difference between the last year's benchmark median compensation minus the firm's compensation last year (CDF Distance). CDF Distance is positive if last year's CEO pay was below the peer group median and is negative when last year's pay was above the peer group median.

The benchmark group formation closely follows BLN, and is based on industry and size. Each year and within each of the 48 industry groups, we classify firms as being in one of two industry size groups: namely the large (small) firm group if they have market capitalization above (below) the industry median. Each firm's benchmark group is then given by all firms in the same industry-size group, such that with 48 industry groups, there are 96 industry-size groups.

The control variables include performance measures (return on equity in the previous year, change in log shareholder value from previous year and growth in log sales) as well as CEO tenure. As GL suggests that changes in the distribution of firm size across large firms in the economy affect CEO compensation, we also include as control variables the market capitalization of the 250th largest firm in the current and the previous year. We further add the

Herfindahl concentration index based on sales to control for the product market structure.[7] Finally, we add the firm's stock price volatility and its market beta (both based on the last 5 years) to control for differences in risk, which may be particularly important for the valuation of the option packages (see also Aggarwal and Samwick 1999a). However, these additional controls (i.e., those not included in BLN) do not significantly affect the implications of our methodological changes.

We propose two methodological changes relative to BLN. The first is relatively innocuous and consists of considering log compensation rather than compensation. While results are largely similar across these specifications, results using log compensation are less sensitive to outliers and small sample problems, and the skewness of the regression residual errors is no longer rejected as consistent with the normal distribution in the case of using compensation (results available upon request).

The second methodological change we propose is more critical. Specification (1) assumes that, after controlling for the performance, tenure, and economy-wide variables, changes in compensation follow a random walk. However, this ignores the very significant positive autocorrelation of firms' CEO compensation across time. For example, a pooled panel regression of log CEO compensation on a constant and its one-year lag gives an R^2 of 56% and an AR(1) coefficient of 0.76, which is quite significantly smaller than 1. Because of this, the first difference of (log) compensation has very significantly *negative* autocorrelation. For negatively autocorrelated variables, a relatively low (high) value tends to be followed by a subsequent increase (decrease). Therefore, without adjusting changes in (log) compensation for strong negative autocorrelation, there is, by construction, a large positive association between changes in compensation and both CEO compensation distance proxies described above. In particular, negatively autocorrelated changes in (log) compensation mean that firms with previous

[7] The Herfindahl is calculated using all Compustat firms and for the Fama-French 48 industry groups.

compensation decreases tend to increase their compensation the subsequent year. However, firms with previous compensation decreases are also more likely to have low compensation relative to their benchmark, such that this negative autocorrelation, if not corrected for, could significantly increase evidence for benchmarking.

Fortunately, such effects are relatively easy to correct for by controlling for the lagged level of CEO compensation. Note that controlling for the lagged level of CEO compensation should not affect the evidence for benchmarking in a well-specified regression. Benchmarking specifically links the change in CEO compensation to its distance to the compensation of *other* firms, not its distance to its *own* lagged compensation.

Table 4 shows the importance of controlling for the lagged level of CEO compensation in the benchmarking regressions similar to those run in BLN, using changes in log CEO compensation as the dependent variable and the Low Compensation Dummy (in Panel A) and CDF Distance (in Panel B) as the benchmarking proxies. In the first two columns of each panel, the specifications do not control for lagged compensation. The lagged compensation is then added in the last two columns. Throughout the paper, robust standard errors clustered by firm are used and only include CEOs with at least 2 years of tenure to make sure that all compensation changes are for the same CEO.

In Panel A, the coefficient on the Low Compensation Dummy equals 0.458 and is highly significant in column 1, and is hardly affected by adding industry dummies in column 2. However, controlling for lagged compensation in column 3 lowers the coefficient on the benchmarking dummy to 0.017, which is insignificant (p-value of 30%). Once industry dummies are added in column 4, the coefficient on the Low Compensation Dummy equals -0.006 (thus with the opposite sign) and is insignificant. In contrast, the lagged compensation variable is highly significant and its addition almost doubles the R^2. The results in Panel B using CDF Distance as the proxy for benchmarking likewise show a very strong reduction in the evidence for benchmarking once lagged compensation is controlled for: the coefficient on CDF Distance drops by about 90%, from 1.010 (column 2) to 0.0093 (column 4), where it is only statistically significant at the 5% level.

Without taking logs, the results are even stronger (results unreported but available upon request). For example, the coefficient on the Low Compensation Dummy equals $1,743 without controlling for lagged compensation (similar to the results in BLN), but changes to -$342 with the control, i.e., with the opposite sign. The same sign reversal happens for the CDF Distance as the proxy for benchmarking.

Overall, once lagged compensation is controlled for, we find much weaker or no evidence for benchmarking. In the next subsection, we will explore whether there is more evidence for benchmarking across different industries depending on each industry's CEO talent pool structure.

3.2 Benchmarking and CEO Talent Pool Structure

Our main goal is to explore how important are peer groups in determining CEO compensation. We previously documented that CEO talent comes from pools that are clearly distinct by industry, with significant differences in the number of insiders across industries. To form the analysis in this section, we divide industries into quartile groups based on their CEO talent pool structure. First, we divide industries into quartile groups based on the percentage of new CEOs across the whole sample who are insiders.[8] The dummy indicating firms in the 25% of industries where CEO talent pools are mostly firm-specific, i.e., where the large majority of CEO candidates come from inside the firm, is denoted as the "high-insider" (percentage) group

[8] We use the whole sample to reduce noise and because there is almost no time variation in the percentage of insiders across industries.

dummy, and the dummy for firms in the bottom quartile of insider CEOs is the "low-insider" group dummy.

Second, we divide industries into quartile groups based on the percentage of new *outsider CEO*s who come from firms in the same industry. The dummy for firms in the 25% of industries where the CEO talent pool is most industry-specific is denoted as the "high-outsider-industry" group dummy, and the dummy for firms in the 25% of industries with the fewest new outsider CEOs from within the industry is the "low-outsider-industry" group dummy.[9] The high-insider and the low-outsider-industry dummies are naturally correlated (35%), and likewise the low-insider and the high-outsider-industry dummies (32%).

In a competitive labor market, one would expect the CEO compensation of firms in the "low-insider" and the "high-outsider-industry" group to be most affected by benchmarking against other firms with a similar size in their industry. For these groups, there are significant outside opportunities for the CEOs, while those firms also have to remain competitive in their ability to attract top talent from other firms. Once both are incorporated simultaneously, one would expect the high/low-insider dummies to become first-order effects, while the high/low-outsider-industry dummies would capture the importance of having outsiders from within the industry or from outside the industry.

We interact the two benchmark proxies with the four CEO talent pool structure dummies, and present the results in Table 5. Panel A shows the regressions using the Low Compensation Dummy as our proxy for benchmarking. The first column shows the unconditional benchmarking results as in Panel B of Table 4 with some additional controls and industry dummies. The first added controls are a dummy indicating whether the CEO is an outsider, the percentage of insiders and the percentage of outside CEOs from the same industry, which are

[9] We again use the Fama-French 48 industries, and use CEO replacements from the whole sample. Dividing the time-series into three sub-periods and calculating the percentage of insiders and of outsiders-from-the-same-industry gives similar results. Also, because we create industry quartile groups, the number of firm-years in each group is slightly different from 25%, but all four groups have between 23% and 25% of firms.

later used to interact with the benchmarking dummies. In the next two columns, we interact the benchmarking proxy with the "high/low insider" and the "high/low-outsider-industry" dummies, without and with industry fixed effects in the second and third column, respectively.

In column 1 of Panel A, the coefficient of the Low Compensation Dummy by itself (i.e., without interaction) is insignificant, as before. While Murphy and Zabojnik (2007) find that outside CEO are paid more (in levels), the compensation changes of outside CEOs are higher, but the effect is not significant.[10] We also find a marginally significant industry-wide effect that a lower percentage of insiders in the industry is associated with greater increases in compensation. Further, CEO compensation changes in concentrated industries are higher.

Column 2 shows that there is still significant evidence for benchmarking in industries with many outsiders. The Low Compensation Dummy is significantly positive and relatively large (coefficient of 0.102) when interacted with the Low Insider Dummy. In contrast, its interaction with the High Insider Dummy is not significant, nor is the proxy by itself (i.e., without interaction) significant. Further, it is only the percentage of insiders in the industry that seems to matter for benchmarking, not whether any such outsiders come primarily from the same industry. Finally, column 3 indicates that these results are robust to adding the industry fixed effects. Therefore, there is no evidence for benchmarking in industries where the CEO is coming mostly from within the firm, but when a large percentage of CEOs in the industry are from outside the firm, benchmarking seems an important part of compensation dynamics. In fact, because the unconditional effect is not significant, evidence for benchmarking exists *exclusively* in industries with many outsider CEOs.

Panel B has the analogous results using the CDF Distance measure as our proxy for benchmarking. The results are quite similar to those in panel A: once industry fixed effects are

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[10] The p-value on the Outside CEO Dummy is about 12%. The coefficient on the Outside CEO Dummy is positive and significant at the 5% level if one does not control for stock market volatility.

included, benchmarking is only significant for firms in industries with many outsider CEOs. Adding the Outside CEO Dummy to the specification with industry fixed effects (column 1) makes the coefficient on the CDF Distance by itself insignificant, such that there is no longer unconditional evidence for benchmarking. Further, the differences in benchmarking between industries with many and few outside CEOs in column 3 are particularly large, namely 19% more and 13% less likely than on average, respectively.

Our results contribute to the findings of BLN in two ways. First, we show that adding lagged compensation to the explanatory variables essentially takes away the average effect of benchmarking on the dynamics of executive compensation. Second, we also show that in the subset of firms with high percentage of outsider CEOs, there is still very strong evidence for benchmarking. Because the unconditional effect is not significant, evidence for benchmarking exists *exclusively* in industries with many outsider CEOs, which is consistent with competitive benchmarking and CEO labor market considerations.

4. Pay-for-Luck

CEO compensation may change not only with firm-specific performance, but also with the industry or even economy-wide performance. This finding stands in seeming contrast to the intuition of e.g. Holmstrom (1979) that CEOs should only be paid for the part of performance that they can influence (denoted by “Skill”), and not for the performance that is due to other factors such as industry-wide shocks (denoted by “Luck”). Bertrand and Mullainathan (2001) argue that ‘pay for luck’ is a manifestation of an agency conflict. In contrast, Himmelberg and Hubbard (2000) and Hubbard (2005) argue that pay for luck can be due to the correlation between the value of CEO skill and market conditions. When the industry is booming, the value of CEO skill increases and therefore the CEO should receive higher compensation.

In this section, we explore the relation between pay for luck and the structure of CEO talent pools. To the extent that pay for luck is the result of changes in the value of CEO skills, shocks within pools, rather than outside pools, should explain CEO compensation. Specifically, in an industry with many outsider CEOs and where the overall supply of CEOs will be relatively inelastic, boards may be forced to raise their CEOs compensation if there is a positive industry-wide shock. An industry-wide boom clearly improves each CEO's next best alternative in those industries. However, in industries with very few outsider CEOs, such a competitive labor market argument would be less compelling, if CEOs and top executives are beholden to the firm and (almost) never move to outside opportunities.

4.1 Methodology for Measuring Pay-for-Luck

Our measure of performance is the firms' annual excess stock return (dividends reinvested, above the risk-free rate). This measure has a large explanatory power for cross-sectional variations in CEO compensation (Jensen and Murphy 1990), and is commonly used. To separate the component of performance that is due to luck from the component that is due to skills, our two-stage regression closely follows Garvey and Milbourn (2006) and BLN. In the first stage, we conduct a pooled panel regression of annual firm excess stock returns on value- and equally-weighted industry excess stock returns, industry dummies and year dummies.[11] Next, the estimated coefficients are used to calculate the component of the return that is explained by the industry returns and the industry and year dummies. As in Garvey and Milbourn (2006) and BLN, we define this fitted component as the "luck" component of the return, which is

[11] We use both equal-weighted industry returns and value-weighted industry returns in the regression to ensure that our results are not biased because of size distribution within industries. We tried both French's 48 industry classification of industries and the 10 industry classification in the first stage. We found that the skill component using the 48 industry classification is correlated with the luck component using the 10 industry classification, but not the other way around. Therefore, the 48 industry classification seems to be too narrow to fully separate the skill component from the luck component. We therefore use the 10 industry classification in the first stage.

not explained by the firm-specific CEO skills. The regression residual, i.e., the difference between the annual return and the luck component, is denoted as the “skill” component. We then scale these two components of the return by the log of the market capitalization of the firm in the beginning of the year. We define these two components as Skill and Luck.

Both Garvey and Milbourn (2006) and BLN employ industry returns based on 2-digit SIC classifications, where is very similar to using the 48 Fama-French industry groups. This assumes that industry-wide shocks are best captured at this level of industry aggregation, rather than using broader or narrower industry groups. However, if systematic performance shocks tend to affect industries across the 2-digit or the 48 Fama-French industry groups, then using those narrower industry groups could overestimate the Skill component.

Panel A of Table 6 shows the difference between using 10 or 48 Fama-French industry groups. In column 1 and 2, the results for the first-stage pooled panel regressions of annual firm stock returns on value- and equally-weighted industry stock returns (plus industry dummies and year dummies) are presented using 10 and 48 industry groups, respectively. Interestingly, the R^2 using 10 industry groups is much higher (20%) than using 48 industry group (7%), even though the latter includes the fit of 48 dummies.

Next, in columns 3 and 4, we regress the residual (‘skill’) part of columns 1 and 2, respectively, on the value- and equally weighted returns of the 48 and 10 industry groups, respectively. If the estimated residual parts are indeed skill or firm-specific, then these regressions should result in a very poor fit. And indeed, regressing skill from the 10 industry groups (i.e., the residual from column 1) on the industry returns from the 48 industry groups results in an R^2 of 0.93% with neither the value- or the equally weighted returns being significant. However, regressing skill from the 48 industry groups (i.e., the residual from column 2) on the industry returns from the 10 industry groups shows that a considerable part of those skill estimates can be explained by the broader industry grouping: the R^2 equals 14% and both the value- or the equally weighted returns are very significant. Therefore, we conclude that using 48 industry groups tends to severely underestimate how systematic shocks are, such that we will use the results using 10 industry groups to estimate Skill and Luck.

In the second stage, we regress changes in log compensation on Skill and Luck plus controls, year dummies and firm fixed effects. We further interact the proxies of Skill and the Luck with the high/low-insider, and the high/low-outsider-industry dummies. The controls are similar to those used in the benchmarking test.

4.2. Results

The results of the second stage are given in Panel B of Table 6. The first column includes only the cumulative distribution function of CEO volatility as a control (similar to BLN), while the second column includes the other control variables from Table 5 including lagged CEO compensation. Both Skill and Luck have significant and economically large effects on CEO compensation. Using column 2, a 1% increase in the Skill component of performance is associated with a 2.9% increase in compensation, and a 1% increase in the Luck component is associated with an about 1.2% increase in compensation.

Column 3 and 4 show the effect of CEO talent pool structure. In column 3, we interact Skill and Luck with dummies for whether the industry has a high and low percentage of inside CEOs. We find that Skill remains significantly different from zero, but there is no significant difference in the elasticity of compensation changes to the firm-specific component of performance (i.e., Skill) across industries with high and low percentages of insiders. In contrast, Luck or the industry-wide performance component is statistically significant from zero *only* in industries that have a low percentage of insider CEOs, while Luck by itself and interacted with the “high-insider” dummy is insignificant. This result is consistent with the argument that pay-for-luck is driven by outside opportunities to the CEO. When the pool for CEOs is largely other executives within the firm, CEO compensation does not respond to Luck or the industry-wide performance component of compensation.

The last column shows variation in the relation between Skill and Luck across industries with high and low level of CEOs from the same industry. We do not find a variation in the two components across this classification of industries. Our interpretation for this result is that what matters is whether the CEO skill is firm-specific. Whether CEOs are coming from the same industry or from other industries still leaves them with outside opportunities that are affected by industry shocks. These results are also consistent with the benchmarking results in section 3.

5. Talent Pools, Firm Size, and CEO Skill

Gabaix and Landier (GL) analyze the relation between managerial talent and CEO compensation. In their general-equilibrium setting, all firms choose managers from the same pool of talent. Following the insight of Rosen (1992) that productivity of talent increases with firm size, their matching model implies a relation between CEO compensation and the size distribution across large public companies. Empirically, their results rely on the assumption of firm size proxying for CEO talent.

Under some mild distributional assumptions of firm size in the economy, GL show that the compensation to the CEO should be related both to the size of the firm in which the CEO operates and the size of the n^{th} largest firm in the economy, where n is a constant. They then test this prediction using the following specification on a panel of large public US firms

$$Log\ (CEO\ compensation_{it}) = a_0 + a_1\ Log(Size_{it}) + a_2\ Log(Size\_Reference\_Market_t) + e_{it}$$

The variable $Size\_Reference\_Market_t$ is the size of the m^{th} largest firm in the economy. Theoretically, m could be any size ranking as long as it captures the tail of the size distribution.

In their empirical specification, GL use m=250 (the 250th largest firm is the reference firm). GL acknowledge that if talent pools are segmented, then "…the reference firm size should be industry-specific which will lead to an attenuation bias in the coefficient on the reference firm size" (GL page 35).

In this section, we wish to explore the extent to which firm-specific and industry-specific variations in CEO talent pools help explain variations in the compensation. Previously, we documented large differences in CEO talent pools across industries. In pools of CEO candidates that are highly segmented, the GL model would predict that what matters is not the size distribution of firms in the whole economy, but the size distribution of firms within the particular talent pool.

To test the effect of the industry specific talent, we first run the following regression over the entire Execucomp data between the years 1993-2005:

$$Log\ (CEO\ compensation_{it}) = a_0 + a_1\ Log(Size_{it}) + a_2\ Log(Size\_Reference\_Market_t) + a_3\ Log(Size\_Reference\_Industry_t) + e_{it}$$

This specification is similar to GL, except that we add an additional reference firm which is industry specific. Size_Reference_Industry is the size of the 20th largest firm in Compustat that belongs to the same industry as the CEO's firm (using the 48 industry specification of Fama and French (1997)). We define firm size as the market value of the equity of the firm (as this gives clearly higher R^2 than using total cap that includes the book value of debt, as used in GL).

5.1 Market and Industry Reference Firm Size

Table 7 shows the results. Column 1 shows the results of the GL specification. As expected, the coefficients of both market size and the size cohort are significant. Column 2 shows the GL results once we introduce industry-specific reference firms. For each of the 48 industries we find the size of the largest 20^{th} firm (using all firms in the Compustat database, not just those firms in the ExecuComp sample). The size of the largest 20^{th} firm is used as an additional explanatory variable to help explain variation in compensation over time. The results show that variations in the size of the industry-reference firms do not explain any variation in the CEO compensation. The coefficient is not statistically different than zero. In contrast, the market reference firm is still statistically significant from zero.

One interpretation of these findings is that the markets for CEO talent are integrated and therefore the change in the size distribution of firms across the entire economy is the relevant indicator for the change in the return to talent in our sample. However, this result seems inconsistent with our documentation that the labor market for CEO is relatively fragmented. To further explore the result we check whether the effect of the market reference firm or the industry reference firm will differ between industries with high percentage of CEO insiders and industries with high percentage of CEO insiders. We expect firms in industries with a high percentage of CEO insiders to be affected less by reference size variables because, to the extent that these reference size variables represent distribution of skill in top firms, these should be less relevant when the market for talent is firms specific.

We repeat the strategy in the previous sections, and interact each of the variables in equation 4 with whether the firm belongs to industry with high percentage of insider CEOs (top quartile) or to industry with low percentage of insider CEOs (bottom quartile). We also add the percentage of insiders in the industry as a control variable to capture any effect of insiders on compensation levels, not captured by the interaction terms.

Column 3 shows that, overall, there is a small effect of the CEO talent pool on the coefficients of firm size, and the size of the reference firms both in the economy and in the industry. However, we find very limited support for the hypothesis that the importance of the industry and market reference firm sizes should depend on the CEO talent pool structure. Firms that belong to industries with a high percentage of insiders are slightly less affected by variations in economy-wide reference firm size than firms with low-percentage of insiders, but the coefficient and thus the economic significant of the effect is quite small. Further, the effect of the industry reference firm goes in the opposite direction, where we find a slight positive relation between the percentage of insider CEOs in the industry and industry reference firm size, as the coefficient of the interaction between industry reference firm and the high-insider dummy is significantly larger than the coefficient of the interaction between industry reference firm and the low-insider dummy.

5.2 Compensation of Constant-Size Cohorts

Overall, the findings using GL specification stand in contrast to our previous findings that not only CEO talent pools are often quite segmented, but also that firm-specific talent pools respond very little to market wide or industry wide shocks. One possibility for the different findings is that the market capitalization of the reference firms is perhaps not fully capturing CEO talent, but perhaps other variables that are outside their model.

GL's measure of talent is firm size, and their model explains the relative compensation of CEOs by their relative firm size. Thus, for every two firms, their relative compensation will be determined by their relative size. We wish to capture changes in compensation that are orthogonal to shifts in firm size. To capture potential shifts in compensation outside the firm-size distribution, we introduce into GL specification another variable, which is a CEO compensation index of a constant size cohort, choosing relatively small size (i.e., lower talent according to GL) firms of a particular firm size.

Our proxy for the general trend in compensation that are unrelated to the distribution of firm size is the median CEO compensation of firms that belong to a smaller-size cohort. Every year, we sort all firms in Execucomp by market capitalization (adjusted for inflation using 2005 as the base year). We then extract from the sample all firms that have market capitalization between $500 million and $1 billion.[12] We define the median compensation of CEOs in this restricted sample as the CEO compensation index of small size cohort. Another possible interpretation of this median compensation of a constant-size cohort is that it captures general CEO pay inflation. As Aït-Sahalia, Parker and Yogo (2004) point out, the (very) rich consume goods whose prices often behave quite differently from basic consumption goods. [Martijn: Not clear..]

According to GL, the increase in compensation in recent years is not due to change in compensation of any group with a constant-size, but instead due to the shift in the size distribution of the firms in the economy. Thus, adding this variable into the regression should not have an effect on the coefficient of the market cap reference firm.

Table 8 shows the regression results once we introduce the compensation index of the constant-size cohort. The table shows that shifts in the compensation index capture much of the variation in CEO compensation in the economy, and takes away much of the explanatory power of the reference firm size of GL. In the following columns we repeat the analysis using other constant-size cohorts, and the results are robust to the different specifications.

These results cast doubt on the source of variation in compensation in LG's model. It seems that the source is coming from changes in compensation of CEOs while keeping size constant, rather than from shifts in size distribution. This general CEO pay inflation proxy seems to be quite important in explaining shifts in CEO compensation. Understanding the source of the variation in compensation of the constant-size cohorts is left for future research.

[12] Our choice of $0.5-$1 billion is random. We also check the robustness of our measure using other ranges of market capitalizations and find very similar results.

6. Conclusion

Under the assumption of homogenous skills across CEOs and no other frictions, we should observe that the vast majority of new CEOs are coming from outside the firm. The reason is that the market for potential CEOs from outside the firm is much larger than the market for potential CEOs inside the firm, and therefore the likelihood that the best match would come from outside the firm would seem to dwarf the likelihood that the best match comes from inside the firm. We present evidence that is inconsistent with this view. CEO talent pools seem generally be highly industry-specific as well as firm-specific. This large fragmentation can be the result several reasons, such as unique CEO skills that are acquired only through experience in the firm, asymmetric information about potential candidates from outside the firm, entrenchment of insider managers and others.

The fragmentation has important consequences for setting CEO compensation. And indeed, we only find strong evidence for benchmarking for firms in industries in which CEO talent pool is *least* firm specific, or where there are most outside CEOs. Therefore, in those industries benchmarking is consistent with a competitive labor market, where firms adjust the compensation of the CEO to that of others in the industry (Oyer 2004). The lack of evidence for benchmarking in industries with few outsiders suggests lack of evidence for opportunistic pay-setting practices, or CEOs being compensated without regard to performance.

Next, we find that CEO talent pools relate to whether CEO compensation changes not only with firm-specific performance ('skill'), but also with the industry or even economy-wide performance ('luck'). Following the methodology of Garvey and Milbourn (2006) and Bizjak, Lemmon, and Naveen (2008), we only find evidence for pay-for-luck in industries with most outsiders. Intuitively, this suggests that in an industry with many outsider CEOs and where the overall supply of CEOs will be relatively inelastic, boards may be forced to raise their CEOs compensation if there is a positive industry-wide shock. An industry-wide boom clearly improves each CEO's next best alternative in those industries.

Finally, our results question the use of firm size as a proxy for the relative talent of different CEOs (Rosen 1992) and the interpretation of the empirical results in Gabaix and Landier (2008). Their model and specification assume homogeneity in CEO skills across firms, while their empirical results reply on the assumption that firm size can proxy for CEO talent. Having documented the importance of heterogeneous firm- and industry-specific skills, we find that variations in firm size (used as a proxy for talent in GL) within industries explain only a very small portion of the variation in CEO compensation over time. To directly test whether the market reference firm size indeed captures the importance of changes in the distribution of size, we construct a proxy that captures systematic changes in CEO compensation that by construction is not related to the distribution of firm size. In particular, this proxy of the average CEO compensation for a *constant-size* group across time drives out the importance of the reference firm size in explaining CEO compensation. This suggests that the 'size of the reference firm' in GL might capture market-wide CEO pay-inflation not directly related to the distribution of size (or talent) of all firms in the economy.

Overall, our results suggest that there are two important and completely different markets for CEO talent. The first market is external and is composed of managers and CEOs from other companies (largely within the same industry). The second is the internal market for CEOs. To summarize, compensation to CEOs whose market is internal does not respond to industry shocks and is not tied to industry performance. Compensation to CEOs whose market is external responds to industry shocks and is tied to industry performance. Thus, the two views about the drivers of CEO compensation apply, but to different situations and to different industries.

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TABLE 1: DATA CONSTRUCTION

The table shows the construction of the database of new CEOs. The sample consists of all CEOs in the Execucomp database between 1993 and 2005. From that sample, a subsample of new CEOs was extracted. The final sample of new CEOs consists of 1,827 persons.

Total number of Execucomp firm years (93-05):	24,084
Firm years with unidentifiable CEOs	2,745
Total number of firm years with CEOANN	21,339
Identifying additional CEOs:	2,064
Total firms with CEO info:	23,403
Number of firm-years with new CEOs:	1,890
No proxy information about the past experience of the CEO	63
Total number of firm years with New Ceos that have available data	1,827

TABLE 2: CHARACTERISTICS OF NEW CEOS

The table shows the characteristics of new CEOs in the Execucomp database. Panel A shows the distribution of new CEOs by Insiders, Outsiders, and Interim. Insider CEOs are CEOs whose previous position in the previous two years was with the same company. Interim CEOs are new CEOs who were replaced within a year from becoming CEOs, or who declared in the proxy statement that they are interim CEOs once they took their position. In panels B, C, and D, the information about previous employment of the CEOs is from the proxy statements, which provides information about the employment history of the CEO within the past five years. If the CEO's past employment was for less than 6 months, we take the previous employment record.

Panel A: Insiders, Outsiders, and Interim CEOs

Period	All CEOs	Insiders	Outsiders	Interim
1993-1996	498	312	152	34
		63%	31%	7%
1997-1999	463	284	146	33
		61%	32%	7%
2000-2002	466	313	122	31
		67%	26%	7%
2003-2005	400	238	127	35
		60%	32%	9%
1993-2005	1,827	1,147	547	133
		63%	30%	7%

Panel B: Former Employment of Outsider CEOs

Period	Total Outsiders	Former CEOs	Former CEOs from Public Firms	Former CEOs from private Firms	Former Non CEOs	Former Non CEOs from Public Firms	Former Non CEOs from Private Firms
1993-1996	152	47	28	19	105	71	34
		31%	18%	13%	69%	47%	22%
1997-1999	146	44	25	19	102	72	30
		30%	17%	13%	70%	49%	21%
2000-2002	122	36	30	6	86	59	27
		30%	25%	5%	70%	48%	22%
2003-2005	127	46	23	23	81	59	22
		36%	18%	18%	64%	46%	17%
1993-2005	547	173	106	67	374	261	113
		32%	19%	12%	68%	48%	21%

Panel C: Former Employment of Outsider CEOs with No Prior CEO Experience

Lower ranked Manager (of a division / subsidiary/VP)	213	43%
COO	40	8%
President	56	11%
CFO	9	2%
Director	18	4%
Investor	4	1%
	340	

Panel D: Former Employment of Insider CEOs

(Note: the sample consists of 599 CEOs, which is about 52% of all insider CEOs)

	Entire period	93-96	97-99	00-02	03-05
Chief Operating Officer	39%	38%	36%	40%	44%
Manager of a division / Vice President	23%	21%	29%	22%	17%
President	20%	29%	19%	17%	14%
CEO of a subsidiary / acquired company	9%	7%	8%	11%	10%
CFO	4%	1%	4%	4%	9%
Owner/Founder	3%	2%	3%	4%	3%
Director	2%	1%	2%	2%	3%
Former CEO of company	1%	3%	0%	1%	1%

TABLE 3: INDUSTRY DISTRIBUTION OF OUTSIDER CEO S

The table shows the distribution of new CEOs across industries from the sample of all new CEOs between 1993 and 2005, and whose firm is in Execucomp, using 10 (Panel A) and 48 industry groups (Panel C). For the outsider CEOs and 10 industry groups, Panel A also shows the number (and as a percentage in two ways: first as the percentage of all CEO coming to that industry, secondly as the percentage of all CEO from that industry) of outsider CEOs who came from a given industry and ended up as CEOs in a different industry. Panel B shows the meaning of the industry abbreviations which are used in Panel A.

Panel A: Transition Matrix of new CEOs

			Industries from which new outsider CEOs come									
Industries where new CEOs go	CEO Insiders	CEO Outsiders	NoDur	Durbl	Manuf	Enrgy	HiTec	Telcm	Shops	Hlth	Utils	Other
NoDur	76	28	18	0	3	0	0	0	1	0	0	6
	73%	27%	64%	0%	11%	0%	0%	0%	4%	0%	0%	21%
			49%	0%	4%	0%	0%	0%	2%	0%	0%	4%
Durbl	50	18	1	9	3	0	0	0	2	0	1	2
	74%	26%	6%	50%	17%	0%	0%	0%	11%	0%	6%	11%
			3%	45%	4%	0%	0%	0%	4%	0%	4%	1%
Manuf	206	85	7	6	42	3	14	0	1	3	0	9
	71%	29%	8%	7%	49%	4%	16%	0%	1%	4%	0%	11%
			19%	30%	54%	30%	12%	0%	2%	8%	0%	6%
Enrgy	44	9	0	1	1	4	0	0	0	0	2	1
	83%	17%	0%	11%	11%	44%	0%	0%	0%	0%	22%	11%
			0%	5%	1%	40%	0%	0%	0%	0%	8%	1%
HiTec	186	152	6	1	13	0	86	10	3	3	1	29
	55%	45%	4%	1%	9%	0%	57%	7%	2%	2%	1%	19%
			16%	5%	17%	0%	74%	53%	7%	8%	4%	21%
Telcm	24	11	1	0	0	0	3	6	0	0	0	1
	69%	31%	9%	0%	0%	0%	27%	55%	0%	0%	0%	9%
			3%	0%	0%	0%	3%	32%	0%	0%	0%	1%
Shops	133	65	3	2	5	0	5	1	33	4	0	12
	67%	33%	5%	3%	8%	0%	8%	2%	51%	6%	0%	18%
			8%	10%	6%	0%	4%	5%	72%	11%	0%	9%
Hlth	71	39	0	0	4	0	0	0	1	26	0	8
	65%	35%	0%	0%	10%	0%	0%	0%	3%	67%	0%	21%
			0%	0%	5%	0%	0%	0%	2%	72%	0%	6%
Utils	86	23	1	0	1	0	1	1	0	0	18	1
	79%	21%	4%	0%	4%	0%	4%	4%	0%	0%	78%	4%
			3%	0%	1%	0%	1%	5%	0%	0%	72%	1%
Other	269	96	0	1	6	3	7	1	5	0	3	70
	74%	26%	0%	1%	6%	3%	7%	1%	5%	0%	3%	73%
			0%	5%	8%	30%	6%	5%	11%	0%	12%	50%
Total	1145	526	37	20	78	10	116	19	46	36	25	139

Panel B: Industry list

NoDur	Consumer NonDurables -- Food, Tobacco, Textiles, Apparel, Leather, Toy
Durbl	Consumer Durables -- Cars, TV's, Furniture, Household Appliances
Manuf	Manufacturing: Machinery, Trucks, Planes, Chemicals, Off Furnishing, Paper, Commercial Printing
Enrgy	Oil, Gas, and Coal Extraction and Product
HiTec	Business Equipment, Computers, Software, and Electronic Equipment
Telcm	Telephone and Television Transmission
Shops	Wholesale, Retail, and Some Services (Laundries, Repair Shops)
Hlth	Healthcare, Medical Equipment, and Drugs
Utils	Utilities
Other	Other -- Mines, Construction, Building Materials, Trans, Hotels, Bus Services, Entertainment, Finance

Panel C: Insiders, outsiders, and outsiders in similar industry – 48 industry classification

	Industry	Total	Total Insiders	Total outsiders	Total outsiders from the same industry	% insiders	% insiders or outsiders from same industry
1	AGRICULTURE	4	3	1	0	75%	75%
2	FOOD PRODUCTS	33	18	15	8	55%	79%
3	CANDY & SODA	7	5	2	0	71%	71%
4	BEER & LIQUOR	11	9	2	0	82%	82%
5	TOBACCO PRODUCTS	5	3	2	0	60%	60%
6	TOYS AND RECREATION	10	7	3	0	70%	70%
7	FUN AND ENTERTAINMENT	20	15	5	0	75%	75%
8	BOOKS	18	12	6	1	67%	72%
9	CONSUMER GOODS	34	23	11	0	68%	68%
10	APPAREL	19	13	6	3	68%	84%
11	HEALTHCARE	24	16	8	4	67%	83%
12	MEDICAL EQUIPMENT	35	27	8	5	77%	91%
13	PHARMACEUTICAL PRODUCTS	48	28	20	11	58%	81%
14	CHEMICALS	55	37	18	10	67%	85%
15	RUBBER AND PLASTIC PRODUCTS	9	5	4	0	56%	56%
16	TEXTILES	7	7	0	0	100%	100%
17	CONSTRUCTION MATERIALS	29	22	7	3	76%	86%
18	CONSTRUCTION	13	12	1	1	92%	100%

19	STEEL WORKS ETC	33	28	5	2	85%	91%
20	FABRICATED PRODUCTS	3	3	0	0	100%	100%
21	MACHINERY	62	46	16	4	74%	81%
22	ELECTRICAL EQUIPMENT	32	23	9	3	72%	81%
23	AUTOMOBILES AND TRUCKS	40	26	14	8	65%	85%
24	AIRCRAFT	15	7	8	1	47%	53%
25	SHIPBUILDING, RAILROAD EQUIPMENT	5	4	1	0	80%	80%
26	DEFENSE	1	1	0	0	100%	100%
27	PRECIOUS METALS	8	7	1	1	88%	100%
28	NON-METALLIC AND INDUSTRIAL METAL MINING	6	4	2	0	67%	67%
29	COAL	1	1	0	0	100%	100%
30	PETROLEUM AND NATURAL GAS	52	42	10	4	81%	88%
31	UTILITIES	111	86	25	18	77%	94%
32	COMMUNICATION	43	24	19	6	56%	70%
33	PERSONAL SERVICES	19	10	9	1	53%	58%
34	BUSINESS SERVICES	158	96	62	29	61%	79%
35	COMPUTERS	79	40	39	18	51%	73%
36	ELECTRONIC EQUIPMENT	93	64	29	14	69%	84%
37	MEASURING AND CONTROL EQUIPMENT	38	23	15	5	61%	74%
38	BUSINESS SUPPLIES	35	25	10	2	71%	77%
39	SHIPPING CONTAINERS	7	6	1	0	86%	86%
40	TRANSPORTATION	34	28	6	1	82%	85%
41	WHOLESALE	44	35	9	4	80%	89%
42	RETAIL	101	73	28	17	72%	89%
43	RESTAURANTS, HOTELS, MOTELS	32	20	12	6	63%	81%
44	BANKING	85	68	17	11	80%	93%
45	INSURANCE	66	53	13	8	80%	92%
46	REAL ESTATE	2	0	2	0	0%	0%
47	TRADING	61	25	36	6	41%	51%
48	MISCELLANEOUS	23	15	8	0	65%	65%

TABLE 4: BENCHMARKING

The table shows regression results of changes in log compensation on two benchmarking proxies and controls. In panel A, the benchmark proxy is a dummy variable for whether the CEO compensation last year was lower than the median compensation of its 48-industry-2-size group in the previous year. In panel B, the benchmark proxy is the cumulative distribution function of the median compensation of its industry-size group minus the CEO compensation during the previous year (CDF Distance). TDC1 is the total CEO compensation and is taken from Execucomp. Market Cap_250 is the equity market capitalization of the 250th largest firm in Compustat. Tenure is the number of years since the CEO took place. The numbers in parentheses are robust standard errors clustered at the firm level. ***, **,* represent significance at the 1%, 5%, and 10% levels respectively.

Panel A: Benchmarking – Low Compensation Dummy

Dependent variable: Log(tdc1$_{it}$)-Log(tdc1$_{it-1}$)

Low Compensation Dummy$_{t-1}$	0.458	(0.016)	***	0.461	(0.016)	***	0.017	(0.016)		-0.006	(0.016)	
Log(tdc1$_{t-1}$)							-0.441	(0.020)	***	-0.464	(0.021)	***
Herfindahl Concentration	-0.453	(0.257)	*	-1.699	(0.562)	***	1.403	(0.340)	***	-0.426	(0.600)	
Stock Price Volatility	0.028	(0.042)		0.041	(0.044)		0.209	(0.044)	***	0.217	(0.047)	***
Market Beta	0.000	(0.014)		0.007	(0.015)		-0.007	(0.014)		-0.005	(0.015)	
Log(Sales$_t$)- Log(Sales$_{t-1}$)	0.150	(0.035)	***	0.154	(0.036)	***	0.100	(0.033)	***	0.099	(0.033)	***
ROE	0.006	(0.001)	***	0.006	(0.001)	***	0.006	(0.002)	***	0.006	(0.002)	***
Log(MrketCap$_t$)- Log(MarketCap$_{t-1}$)	0.314	(0.019)	***	0.319	(0.019)	***	0.335	(0.018)	***	0.336	(0.018)	***
Log(MarketCap$_{t-1}$)	0.042	(0.004)	***	0.047	(0.004)	***	0.210	(0.011)	***	0.218	(0.011)	***
Log(MarketCap_250$_t$)	-0.169	(0.050)	***	-0.176	(0.051)	***	-0.113	(0.045)	**	-0.120	(0.045)	***
Log(MarketCap_250$_{t-1}$)	0.153	(0.047)	**	0.149	(0.047)	**	0.314	(0.044)	***	0.316	(0.044)	***
Tenure	-0.002	(0.001)	**	-0.002	(0.001)	**	-0.002	(0.001)	***	-0.003	(0.001)	***
Constant	-0.322	(0.187)	*	-0.220	(0.191)		0.011	(0.187)		0.255	(0.191)	***
Industry Dummies	-			+			-			+		
R^2	0.138			0.139			0.268			0.275		
Observations	11,699			11,699			11,699			11,699		

Panel B: Benchmarking – Cumulative Distribution Function of Distance

Dependent variable: Log(tdc1$_{it}$)-Log(tdc1$_{it-1}$)

CDF Distance$_{t-1}$	1.010	(0.036)	***	1.019	(0.036)	***	0.151	(0.035)	***	0.093	(0.036)	**
Log(tdc1$_{t-1}$)							-0.408	(0.021)	***	-0.436	(0.022)	***
Herfindahl Concentration	-0.304	(0.288)		-1.569	(0.573)	***	1.293	(0.339)	***	-0.481	(0.600)	
Stock Price Volatility	0.097	(0.041)	**	0.119	(0.044)	***	0.209	(0.044)	***	0.218	(0.047)	***
Market Beta	-0.013	(0.014)		-0.005	(0.015)		-0.008	(0.014)		-0.005	(0.015)	
Log(Sales$_t$)- Log(Sales$_{t-1}$)	0.134	(0.034)	***	0.139	(0.035)	***	0.100	(0.033)	***	0.100	(0.033)	***
ROE	0.006	(0.001)	***	0.006	(0.001)	***	0.006	(0.002)	***	0.006	(0.002)	***
Log(MarketCap$_t$)- Log(MarketCap$_{t-1}$)	0.321	(0.018)	***	0.326	(0.019)	***	0.335	(0.018)	***	0.337	(0.018)	***
Log(MarketCap$_{t-1}$)	0.057	(0.005)	***	0.064	(0.005)	***	0.201	(0.011)	***	0.211	(0.011)	***
Log(MarketCap_250$_t$)	-0.159	(0.048)	***	-0.165	(0.048)	***	-0.115	(0.045)	**	-0.122	(0.045)	***
Log(MarketCap_250$_{t-1}$)	0.119	(0.045)	*	0.113	(0.045)	**	0.294	(0.044)	***	0.300	(0.044)	***
Tenure	-0.002	(0.001)	**	-0.002	(0.001)	**	-0.002	(0.001)	**	-0.003	(0.001)	***
Constant	-0.517	(0.186)	***	-0.414	(0.190)	**	-0.050	(0.187)		0.202	(0.191)	
Industry Dummies	-			+			-			+		
R^2	0.189			0.191			0.269			0.276		
Observations	11,699			11,699			11,699			11,699		

TABLE 5: BENCHMARKING AND TALENT POOLS

The table shows regression results of changes in log compensation on two benchmarking proxies interacted with CEO talent pool structure and controls. In panel A, the benchmark is a dummy variable for whether the CEO compensation in the current year is lower than the median compensation of its industry-size group in the previous year. Industry grouping is according to Kenneth French's 48 industry classification. Within each industry and each year, we further classify firms into large and small–size based on whether they are above or below the median equity market capitalization for all Compustat firms within the industry in the particular year. In panel B, the benchmark proxy is the cumulative distribution function of the median compensation of its industry-size group minus the CEO compensation during the previous year (CDF Distance). Low (High) Insider is a dummy variable for whether the industry to which the firm belongs is at the bottom (top) 25% in terms of the percentage of CEOs that are coming from within the firm. Low (High) Outsider Industry is a dummy variable for whether the industry to which the firm belongs is at the bottom (top) 25% in terms of the percentage of outsider CEOs that are coming from within the same industry. The rest of the variables are defined in Table 4. The numbers in parentheses are robust standard errors clustered at the firm level. ***, **,* represent significance at the 1%, 5%, and 10% levels respectively.

Panel A: Benchmarking measure – Low Compensation Dummy

Dependent variable: $Log(tdc1_{it})$-$Log(tdc1_{it-1})$

Low Compensation Dummy $_{t-1}$	-0.020	(0.017)		0.002	(0.022)		-0.023	(0.026)	
Low Compensation Dummy $_{t-1}$ * Low Insider				0.102	(0.033)	***	0.114	(0.037)	***
Low Compensation Dummy $_{t-1}$ * High Insider				0.003	(0.029)		-0.054	(0.034)	
Low Compensation Dummy $_{t-1}$ * Low Outsider Industry				-0.047	(0.032)		0.012	(0.037)	
Low Compensation Dummy $_{t-1}$ * High Outsider Industry				-0.027	(0.033)		-0.039	(0.038)	
Outside CEO Dummy	0.024	(0.022)		0.023	(0.021)		0.024	(0.021)	
Percentage of Insiders in Industry				-0.013	(0.122)				
Percentage of Outside CEOs from Industry				-0.004	(0.002)	**			
$Log(tdc1_{t-1})$	-0.496	(0.021)	***	-0.468	(0.020)	***	-0.492	(0.021)	***
Herfindahl Concentration	-0.177	(0.613)		1.566	(0.413)	***	-0.082	(0.619)	
Stock Price Volatility	0.321	(0.059)	***	0.301	(0.055)	***	0.320	(0.059)	***
Market Beta	0.018	(0.017)		0.015	(0.016)		0.019	(0.017)	
$Log(Sales_t)$- $Log(Sales_{t-1})$	0.104	(0.033)	***	0.107	(0.034)	***	0.104	(0.034)	***
ROE	0.006	(0.004)		0.006	(0.004)		0.006	(0.004)	
$Log(MarketCap_t)$- $Log(MarketCap_{t-1})$	0.319	(0.018)	***	0.318	(0.018)	***	0.319	(0.018)	***
$Log(MarketCap_{t-1})$	0.240	(0.012)	***	0.229	(0.011)	***	0.238	(0.012)	***
$Log(MarketCap\_250_t)$	-0.090	(0.044)	*	-0.083	(0.044)	*	-0.090	(0.044)	**
$Log(MarketCap\_250_{t-1})$	0.342	(0.045)	***	0.345	(0.044)	***	0.349	(0.044)	***
Tenure	-0.003	(0.001)	***	-0.003	(0.001)	**	-0.003	(0.001)	***
Constant	-0.198	(0.213)		-0.458	(0.253)		-0.286	(0.214)	
R^2	0.293			0.286			0.295		
Industry Dummies	YES			NO			YES		
Observations	10,385			10,385			10,385		

Panel B: Benchmarking measure – CDF Distance

Dependent variable: $Log(tdc1_{it})-Log(tdc1_{it-1})$

CDF $Distance_{t-1}$	0.060	(0.037)		0.128	(0.043)	***	0.085	(0.056)	
CDF $Distance_{t-1}$ * Low Insider				0.146	(0.050)	***	0.194	(0.066)	***
CDF $Distance_{t-1}$ * High Insider				-0.029	(0.043)		-0.131	(0.062)	***
CDF $Distance_{t-1}$ * Low Outsider_Industry				-0.126	(0.051)	***	-0.038	(0.075)	
CDF $Distance_{t-1}$ * High Outsider_Industry				0.011	(0.050)		-0.050	(0.075)	
Outside CEO Dummy	0.025	(0.021)		0.023	(0.021)		0.025	(0.021)	
Percentage of Insiders in Industry				0.065	(0.152)				
Percentage of Outside CEOs from Industry				-0.008	(0.003)	***			
$Log(tdc1_{t-1})$	-0.472	(0.022)	***	-0.437	(0.021)	***	-0.463	(0.022)	***
Herfindahl Concentration	0.613	(0.390)		1.495	(0.452)	***	-0.097	(0.621)	
Stock Price Volatility	0.320	(0.059)	***	0.302	(0.055)	***	0.321	(0.059)	***
Market Beta	0.018	(0.017)		0.012	(0.016)		0.020	(0.017)	
$Log(Sales_t)$- $Log(Sales_{t-1})$	0.105	(0.034)	***	0.106	(0.034)	***	0.103	(0.034)	***
ROE	0.006	(0.004)		0.006	(0.004)		0.006	(0.004)	
$Log(MarketCap_t)$- $Log(MarketCap_{t-1})$	0.320	(0.018)	***	0.319	(0.018)	***	0.320	(0.018)	***
$Log(MarketCap_{t-1})$	0.233	(0.012)	***	0.221	(0.011)	***	0.230	(0.012)	***
$Log(MarketCap\_250_t)$	-0.092	(0.044)	**	-0.082	(0.044)	*	-0.089	(0.044)	**
$Log(MarketCap\_250_{t-1})$	0.328	(0.045)	***	0.330	(0.044)	***	0.340	(0.045)	***
Tenure	-0.003	(0.001)	***	-0.003	(0.001)	**	-0.003	(0.001)	***
Constant	-0.242	(0.213)		-0.568	(0.277)		-0.432	(0.217)	
R^2	0.293			0.288			0.296		
Industry Dummies	YES			NO			YES		
Observations	10,385			10,385			10,385		

TABLE 6: PAY FOR LUCK

Panel A shows regression results of annual firm return (dividend reinvested) on industry returns, year dummies, and industry dummies. Industry classification is based on Kenneth French's 10 industry classification (column 1) and 48 industry classification (column 2). Panel B shows the regression results where the dependent variable is the change in Log compensation between the current year and the previous year, including year and firm fixed effects. The variable Luck is the fitted return from the regression in panel A (using the 10 industry classification). The variable Skill is the difference between the annual firm return and Luck. Low insider is a dummy variable for whether the industry to which the firm belongs is at the bottom 25% in terms of the percentage of CEOs that are coming from within their own firm. High insider is a dummy variable for whether the industry to which the firm belongs is at the top 25% in terms of the percentage of CEOs that are coming from within the firm. Similarly, Low (High) Outsider Industry is a dummy variable for whether the industry to which the firm belongs is at the bottom (top) 25% in terms of the percentage of outsider CEOs that are coming from within the same industry. CDF BS Volat is the cumulative distribution of the stock return volatility of the firm relative to all firms in Execucomp, where the volatility is from Execucomp. The rest of the variables are defined in Table 4 The numbers in parentheses are robust standard errors clustered at the firm level. ***, **,* represent significance at the 1%, 5%, and 10% levels respectively.

Panel A: Choice of Industry Classification

Dependent variable:	Firm Annual Return (1)			Firm Annual Return (2)			Residual Firm Return of (1)		Residual Firm Return of (2)		
10-Industry Return (EW)	0.450	(0.062)	***						0.416	(0.067)	***
10-Industry Return (VW)	0.535	(0.057)	***						0.533	(0.068)	***
48-Industry Return (EW)				0.27	(0.137)	***	0.008	(0.040)			
48-Industry Return (VW)				-0.243	(0.178)		0.056	(0.038)			
Year Dummies	+			+			+		+		
Industry Dummies (10)	+										
Industry Dummies (48)				+							
R2	20%			7%			9.3%		14%		
Obs	18,407			18,407			18,407		18,407		

Panel B: Luck, Skill and Talent Pools

Dependent variable: $Log(tdc1_{it})-Log(tdc1_{it-1})$

Skill	3.729	(0.297)	***	2.905	(0.246)	***	3.014	(0.307)	***	3.011	(0.356)	***
Luck	2.746	(0.663)	***	1.248	(0.440)	***	0.590	(0.558)		1.155	(0.542)	***
Skill * Low Insider							-0.278	(0.579)				
Skill * High Insider							-0.032	(0.508)				
Luck * Low Insider							1.507	(0.809)	**			
Luck * High Insider							0.331	(0.840)				
Skill * Low Outsider Industry										0.179	(0.497)	
Skill * High Outsider Industry										-0.559	(0.538)	
Luck * Low Outsider Industry										0.695	(0.817)	
Luck * High Outsider Industry										-0.014	(0.814)	
CDF BS Volat	0.034	(0.058)		0.141	(0.132)		0.135	(0.132)		0.146	(0.132)	
Outside CEO Dummy				0.088	(0.053)	*	0.089	(0.053)	*	0.089	(0.053)	*
Log (tdc1 (t-1))				-0.958	(0.019)	***	-0.958	(0.019)	***	-0.958	(0.019)	***
Herfindahl Concentration				1.565	(0.806)	*	1.500	(0.805)	*	1.592	(0.807)	*
Stock Price Volatility				0.064	(0.214)		0.077	(0.213)		0.055	(0.214)	
Market Beta				0.025	(0.022)		0.024	(0.022)		0.025	(0.022)	
Log_sales_ch				0.167	(0.039)	***	0.168	(0.039)	***	0.167	(0.039)	***
ROE				0.006	(0.004)	**	0.006	(0.004)	*	0.006	(0.004)	*
Log(market cap (t-1))				0.346	(0.019)	***	0.346	(0.019)	***	0.345	(0.019)	***
Tenure				-0.002	(0.002)		-0.002	(0.002)		-0.002	(0.002)	
Observation	11,733			10,373			10,373			10,373		
R2	0.147			0.567			0.567			0.567		

TABLE 7: GABAIX AND LANDIER RESULTS (2008) AND TALENT POOLS

The table shows the results of panel regressions where the dependent variable is the natural log of CEO compensation. The sample consists of all Execucomp firms with CEO compensation information between the years 1993-2005. CEO compensation is the variable tdc1 from Execucomp and it consists of the sum of salary, bonus, value of restricted stock, and Black-Scholes value of option grants for the fiscal year. The independent variable log (Total cap) is the natural log of the market capitalization of the firm at the end of the fiscal year. Market Cap Ref. $Firm_t$ is the total capitalization of the 250^{th} largest firm in the Compustat database. Low insider is a dummy variable for whether the industry to which the firm belongs is at the bottom 25% in terms of the percentage of CEOs that are coming from within their own firm. High insider is a dummy variable for whether the industry to which the firm belongs is at the top 25% in terms of the percentage of CEOs that are coming from within the firm. The industry classification is based on the 48 industries in Fama and French (1997). The numbers in parentheses are the standard deviations of the coefficients. All errors are clustered at the firm level. *** indicates significance at the 1% level.

Dependent variable: $Log(tdc1_{it})-Log(tdc1_{it-1})$									
Log (Market Cap_{it})	0.413	(0.009)	***	0.413	(0.010)	***	0.407	(0.015)	***
Log (Market Cap Ref. $Firm_{it}$)	0.461	(0.030)	***	0.467	(0.030)	***	0.476	(0.032)	***
Log (Market Cap Industry. Ref. $Firm_{it}$)				0.020	(0.014)		0.004	(0.020)	
Log (Market Cap_{it}) * High Insider							0.030	(0.022)	
Log (Market Cap_{it}) * Low Insider							0.004	(0.022)	
Log (Market Cap Ref. $Firm_{it}$)* High Insider							-0.020	(0.027)	
Log (Market Cap Ref. $Firm_{it}$)* Low Insider							0.046	(0.027)	*
Log (Market Cap Ind. Ref. $firm_{it}$)* High Insider							0.037	(0.035)	
Log (Market cap Ind. Ref. $firm_{it}$)* Low Insider							-0.098	(0.034)	***
Percent insiders in industry							-0.032	(0.007)	***
Constant	0.574	(0.278)	**	0.391	(0.284)		0.840	(0.302)	***
R^2	35%			35%			35%		
Observations	18,466			18,466			18,466		

TABLE 8: GABAIX AND LANDIER (2008) AND CONSTANT-SIZE COMPENSATION INDEX

The table shows the results of panel regressions where the dependent variable is the natural log of CEO compensation. The sample consists of all Execucomp firms with CEO compensation information between the years 1993-2005. CEO compensation is the variable tdc1 from Execucomp and it consists of the sum of salary, bonus, value of restricted stock, and Black-Scholes value of option grants for the fiscal year. The independent variable Log (Market cap) is the natural log of the market capitalization of the firm at the end of the fiscal year. Market Cap Ref. $Firm_t$ is the total capitalization of the 250th largest firm in the Compustat database. Tdc1 Size Cohort is the total compensation of the median firm (by size) which belongs to a particular market cap cohort in a particular year. In column 1 the cohort is firms with market capitalization between \$0.5 billion and \$1 billion. In column 2, the cohort is firms with market capitalization between \$1 billion and \$2 billion, and in column 3, the cohort is firms with market capitalization between \$2-\$4 billion. Mkt Cap Size Cohort is the market capitalization of the median firm. All errors are clustered at the firm level. *, **, *** indicate significance at the10%, 5%, and 1% level respectively.

				Mkt Cap Size Cohort $0.5-1 billion			Mkt Cap Size Cohort $1-2 billion			Mkt Cap Size Cohort $2-4 billion		
Log (Market cap_{it})	0.413	(0.009)	***	0.415	(0.009)	***	0.416	(0.009)	***	0.415	(0.007)	***
Log (Market cap Ref. $firm_{it}$)	0.461	(0.030)	***	0.112	(0.042)	***	0.075	(0.047)		0.058	(0.070)	
Log (Tdc1 Size $Cohort)_{it}$				0.908	(0.079)	***	0.880	(0.094)	***	0.616	(0.056)	***
Log (Mkt cap Size $Cohort)_{it}$				-0.189	(0.069)	***	-0.102	(0.043)	**	0.035	(0.074)	
Constant	0.574	(0.278)	**	-1.733	(0.449)	***	-2.015	(0.416)	***	-1.039	(0.888)	
R^2	35%			35%			35%			35%		
Observations	18,624			18,624			18,624			18,624		