Performance-induced CEO turnover

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This paper revisits the relationship between firm performance and CEO turnover. We drop the distinction between forced and voluntary turnovers and introduce the concept of performance-induced turnover, defined as turnover that would not have occurred had performance been "good". We document a close link between performance and CEO turnover and estimate that between 38% and 55% of all turnovers are performance induced, with an even higher percentage early in tenure. This is significantly more than the number of forced turnovers identified in prior studies. We contrast the empirical properties of performance-induced turnovers with the predictions of Bayesian learning models of CEO turnover. Learning by boards about CEO ability appears to be slow, and boards act as if CEO ability (or match quality) was subject to frequent and sizeable shocks.

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Replacing badly performing CEOs is one of the key responsibilities of corporate boards, and the relationship between CEO turnover and firm performance has been studied extensively. The prior literature has found only modest effects of firm performance on forced CEO turnover. Depending on the sample and the performance measure used, the annual probability of a forced CEO turnover is 2 to 6 percentage points higher for a bottom decile than for a top decile performer.[1] This led Jensen and Murphy (1990) and others to conclude that dismissals are not an important source of CEO incentives. Several studies attribute the apparent paucity of forced CEO turnovers after bad performance to entrenchment and weak corporate governance (Weisbach (1988), Hermalin and Weisbach (1998), Taylor (2010)).

This paper does away with the distinction between forced and voluntary turnover and instead introduces the concept of performance-induced turnover, defined as turnover that would not have occurred had performance been "good". Intuitively, the rate of performance-induced turnover at any performance level x is identified from the difference between the turnover rate at x and that at high levels of performance. The assumption is that turnovers at sufficiently high performance levels are unrelated to performance and, thus, would have occurred at any level of performance. Any higher turnover rate at lower performance levels is assumed to be caused by performance being worse. These additional turnovers are labelled as *performance induced*.

We find that, depending on the estimation method, between 38% and 55% of all CEO turnovers are performance induced. This is about twice the fraction of forced turnovers identified in prior studies. The reason for this difference is simple: the prior literature distinguishes forced from voluntary turnovers based on CEO characteristics, especially CEO age, and characteristics of the turnover process.[2] Crucially, these classifications do not use performance to identify forced turnovers. We find that turnovers usually classified as "voluntary" are significantly more frequent at lower levels of performance, suggesting that many of them are in fact performance induced.[3] Figure 1.a illustrates this result using Parrino's (1997) popular classification algorithm: As performance declines, the annual rate of "voluntary" turnover rises from 6.8% above the 95th performance percentile to 13.7% below

[1] See Coughlin and Schmidt (1985), Warner, Watts, and Wruck (1988), Weisbach (1988), Jensen and Murphy (1990), Denis, Denis, and Sarin (1997), Murphy (1999), and Huson, Parrino, and Starks (2001).
[2] See, for example, Warner et al. (1988), Dennis and Dennis (1995), Kim (1996), and Parrino (1997).
[3] See Kaplan and Minton (2012) for consistent evidence.

the 5th percentile. By focusing on forced turnover, the prior literature ignores this increase and underestimates the number of turnovers caused by bad performance.

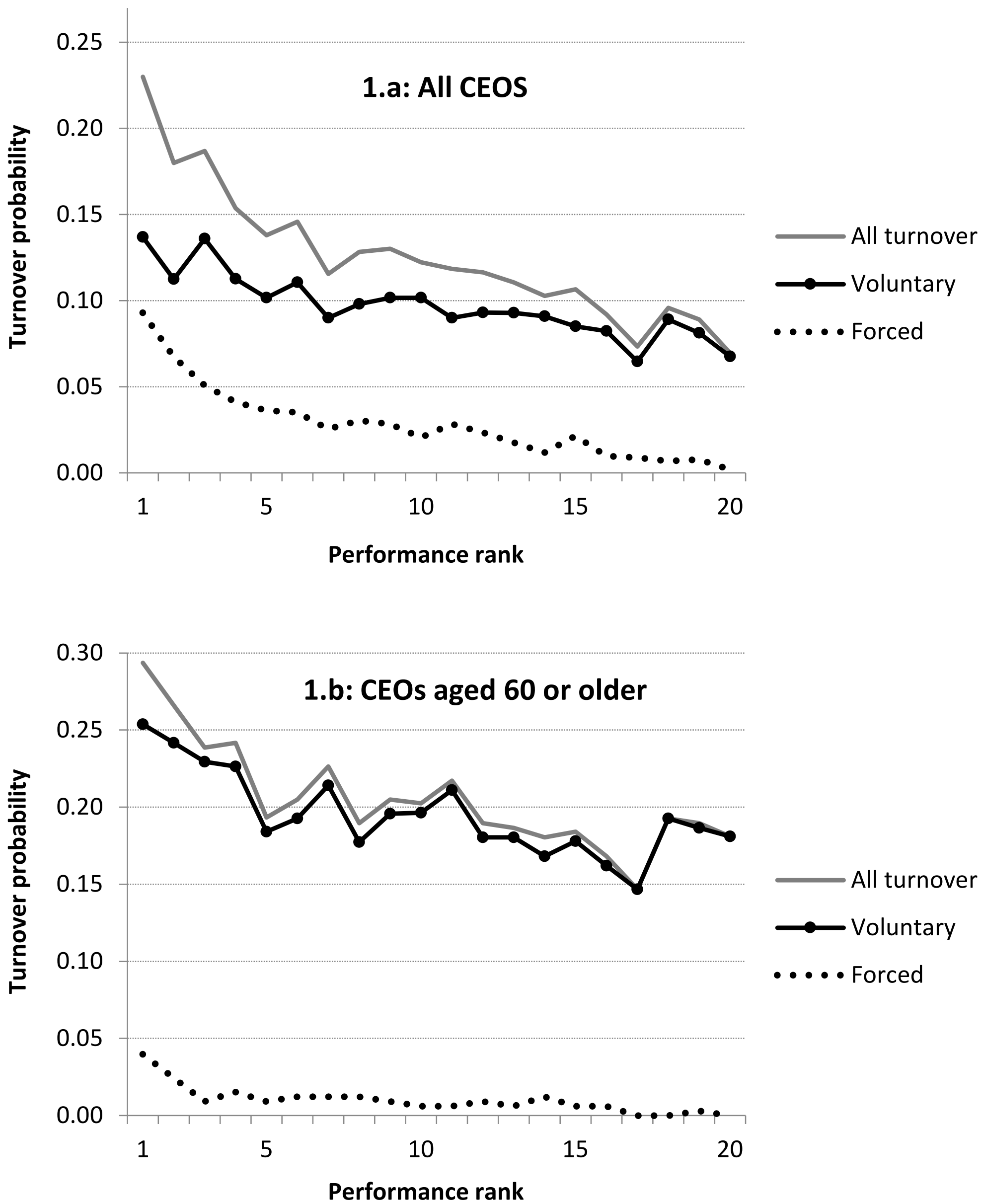

Fig. 1: Probability of forced and voluntary turnover as a function of performance. The figure shows average turnover rates within performance ranks. Performance is measured as the average stock return in years -2 to 0 before the turnover year and is sorted into 20 percentile ranks. Forced turnovers are identified using the Parrino (1997) algorithm.

Shifting attention from forced to performance-induced turnovers also changes how turnover varies with age and tenure, which in turn changes our view of governance dynamics.

Performance-induced turnover is much more stable across tenure than forced turnover. The estimated performance-induced turnover rate is 7.0% in tenure year 2, 6.2% in tenure years 7-8, and 5.3% in tenure years 17 and higher. Forced turnovers decline much more rapidly as tenure increases, from 4.6% in tenure year 2 to 3.3% in years 7-8 and 1.0% in years 17 and higher.

The literature has interpreted the decline of forced turnover over CEO tenure as evidence of increasing entrenchment (Hermalin and Weisbach (1998), Dikolli, Mayew, and Nanda (2014)). Our evidence suggests instead that much of this decline is a mechanical consequence of the classification algorithms: Tenure and age are highly correlated, and almost all algorithms assume that turnovers at or above typical retirement ages are likely to be voluntary. In contrast, we find that even turnovers of retirement-age CEOs are significantly more likely when performance is low. This is illustrated in Figure 1.b, which shows turnover rates for CEOs aged 60 and higher. Based on Parrino's classification algorithm, there are almost no forced turnovers in this age group. The substantial increase in turnover as performance declines is therefore attributed to "voluntary" departures, which are in fact more performance-sensitive than forced ones in this sample. We instead attribute this increase to performance-induced turnover.

We contrast the empirical properties of performance-induced turnovers with the predictions of Bayesian learning models of CEO turnover, which are the theoretical framework most frequently used by the prior literature.[4] The evidence rejects the literature's workhorse model, in which boards learn from firm performance about constant CEO ability. With both ability and the relationship between ability and performance constant, the model predicts that boards assign the exact same weight to all past performance signals. Empirically, performance-induced turnover is driven by performance in the most recent three to four years and is insensitive to older performance signals. Moreover, the sensitivity of boards' beliefs to new performance signals shows little to no decline for at least the first ten years of CEO tenure. The degree to which this sensitivity declines over time measures the degree to which boards' beliefs about CEO ability are becoming more precise. The lack of a decline suggests that boards are unable to figure out CEO ability even after observing performance for many years.

[4] See, for example, Harris and Holmström (1982), Holmström (1982), Murphy (1986), Gibbons and Murphy (1992), Hermalin and Weisbach (1998), Taylor (2010, 2013), and the comprehensive survey by Hermalin and Weisbach (2017).

The evidence is consistent with a version of the Bayesian learning model in which CEO ability is subject to unobserved changes (Kim (1996), Garrett and Pavan (2012)).[5] With changing CEO ability, boards optimally assign larger weights to more recent performance signals, which are most informative about current CEO ability. With changing CEO ability, the variances of boards' beliefs about CEOs also decline more slowly, if at all, and the beliefs remain sensitive to new performance signals even late in tenure.

The shocks to CEO ability that reconcile the Bayesian learning model with the data are large. Even though CEO turnovers are highly sensitive to current performance and performance in the prior year, they are essentially unrelated to performance four or more years ago. This suggests that CEO ability changes sufficiently fast that performance from four years ago is uninformative about CEO ability today. In the same vein, to keep the variance of boards' beliefs, and the sensitivity of those beliefs to new performance signals, constant over time (as suggested by our evidence), the shocks to CEO ability have to be large enough to offset what the board is learning from new performance signals.

Finally, the relationship between turnover and tenure is very different for CEOs than for rank-and-file employees. Performance-induced CEO turnover declines slowly over at least the first 16 years of tenure. Turnover rates for rank-and-file employees peak after 3-6 months of tenure, and then decline rapidly (Farber (1994, 1999)). This suggests that learning about ability is slower for CEOs than for rank-and-file employees. It is, however, also consistent with higher turnovers costs for CEOs, or with larger differences in expected ability between incumbent and replacement CEOs. Both imply that more negative signals need to accumulate before a CEO is replaced, reducing the turnover rate early in tenure and increasing it later.

Performance-induced turnover is identified from two features of the data: the rate of turnover at high levels of performance, which informs our estimate of "other" turnovers unrelated to performance, and the increase in turnover as performance declines. We use two approaches to do the estimation. The first, more conservative approach assumes that the probability of performance-induced turnover is zero at and above some high performance threshold, such as the 90th percentile of the performance distribution. The second approach explicitly estimates two independent turnover processes, one that is affected by performance

[5] These changes might not be to CEO ability per se but to the quality of the CEO-firm match. Match quality might change because of changes to the firm or the firm's environment. We define CEO ability broadly to include match quality in the remainder of the paper.

and goes to zero as performance improves, and one that is not. Because both approaches have advantages and disadvantages, we present results from both in the empirical section.

Performance-induced turnover has two attractive features compared to the forced turnover classifications used in prior studies. First, any algorithm inevitably misclassifies turnovers, and these misclassifications affect the estimated frequency of forced turnover and its relation to firm performance. In contrast, our approach makes no a-priori determination whether a particular departure is forced or voluntary, and instead considers all departures as potentially performance-induced.

Second, performance-induced turnover puts the focus on the extent to which bad performance causes turnover, independently of who initiates the departure, the board or the CEO. This perspective is useful, not only because it avoids biases due to misclassifications, but also because future firm performance is determined by whether bad CEO-firm matches are dissolved, independently of whether the CEO is forced out by the board or not.

It is important to emphasize that performance-induced turnover is a distinct concept from forced turnover, not simply a different estimation method for the same concept. Many CEO departures are forced without being performance induced – e.g., CEOs are fired for backdating options (Lie (2005)). Conversely, many CEO departures are performance induced without being forced – e.g., bad performance causes CEOs to retire early, while outstanding performance convinces CEOs to stay beyond planned retirements. Whether a research project should use performance-induced or forced turnover depends on the question asked. Performance-induced turnover is the right choice if the focus is on whether bad performance causes CEO-firm matches to end.

We proceed as follows. Section 1 reviews Bayesian learning models of CEO turnover and derives testable predictions. Section 2 describes the estimation of performance-induced turnover in detail, while Section 3 describes the data and provides summary statistics. Section 4 presents and interprets the empirical results. Section 5 provides further discussion, and Section 6 concludes.

1 Theoretical framework

1.1 A simple Bayesian learning model of CEO turnover

This section describes a simple Bayesian learning model of CEO turnover. Its ingredients are similar to the more complex models in Jovanovic (1979), Harris and Holmström (1982), Murphy (1986), Gibbons and Murphy (1992), Hermalin and Weisbach (1998), and Taylor (2010). A corporate board hires a new CEO of unobservable and uncertain ability. The board updates its beliefs about the CEO after observing signals of ability, such as firm performance. Negative updates can cause the board to fire the CEO.

We denote the board's initial prior about CEO ability as α_0 and assume that it is normally distributed with mean $\hat{\alpha}_0$ and variance $\frac{1}{\tau_0}$. For simplicity, we set $\hat{\alpha}_0 = 0$. Each period, the board learns from firm performance about CEO ability. Firm performance x_t is given by the CEO's true ability α plus a normally distributed i.i.d. noise term with mean zero and variance $\frac{1}{r}$:

$$x_t = \alpha + \varepsilon_t \quad \text{where } \varepsilon_t \sim N\left(0, \frac{1}{r}\right) \tag{1}$$

The board updates its believes about ability according to Bayes' rule. The mean of the board's posterior estimate of CEO ability is a weighted average of the board's initial prior (normalized to zero) and all signals received since the CEO's hiring. Specifically, after observing performance in period *t*, the posterior mean is:

$$\hat{\alpha}_t = \sum_{i=1}^{t} \frac{r}{(\sigma_{t-1}^2)^{-1} + r} x_i = \sum_{i=1}^{t} \frac{r}{\tau_0 + tr} x_i \tag{2}$$

where σ_{t-1}^2 is the variance of the board's posterior estimate in *t-1*. The board fires the CEO if the posterior mean in year *t* falls below an endogenous threshold $\underline{\alpha_t}$.[6] This simple framework has two testable implications:

1. The board puts equal weight on each of the past performance signals when forming its estimate of CEO ability.

[6] This threshold results from the board trading off the costs of firing the CEO against the expected benefits of replacing him. See Hermalin and Weisbach (1998) and Taylor (2010) for examples.

This prediction follows directly from the assumptions that the CEO's ability, and the relationship between ability and the signal, are constant over time. Intuitively, performance one year ago contains as much information about CEO ability as performance ten years ago.

2. The sensitivity of the board's estimate of CEO ability to any of the performance signals declines with tenure.

In tenure year t, the weight on any prior signal x_i equals $\frac{r}{\tau_0+tr}$, which diminishes with t. Intuitively, the marginal value of each signal decreases as the number of signals increases and the board's beliefs about CEO ability become more precise. Empirically, the speed with which the sensitivity to the performance signals declines with tenure indicates the speed with which the board is learning about CEO ability. We will make use of this insight in the empirical analysis.

1.2 Extension: Changing CEO quality

The models in the prior literature almost always assume that CEO ability is constant.[7] However, CEO ability or, more likely, the quality of the CEO-firm match can change over time due to changes in the firm, its environment, or the CEO himself. In this section, we modify the simple learning model by assuming that the CEO's true ability follows a random walk:

$$\alpha_t = \alpha_{t-1} + \nu_t \tag{3}$$

The i.i.d. shocks ν_t are normally distributed with a mean of zero and variance $\frac{1}{s}$. The random shock ν_t occurs at the beginning of each period t, before the board observes the signal x_t. The board then forms its posterior belief $\hat{\alpha}_t$ and fires the CEO if the posterior mean falls below the threshold $\underline{\alpha}_t$. The model with changing CEO ability has two testable implications:[8]

1. When forming beliefs about CEO ability, boards assign larger weight to more recent performance signals than to older ones.

Intuitively, random shocks to CEO ability increase the importance of current performance signals, which are informative about the most recent shocks, relative to older signals. The rate at which the weights on past performance decline depends on the size of the ability shocks.

[7] See, for example, Harris and Holmström (1982), Murphy (1986), Gibbons and Murphy (1992), Hermalin and Weisbach (1998), and Taylor (2010, 2013). Kim (1996) and Garret and Pavan (2012) are notable exceptions.

[8] The derivation of all results is in Appendix A.

The ratio of the weights on a signal from last period relative to a signal from the current period is $\frac{weight\ on\ last\ period}{weight\ on\ current\ period} = \frac{\sigma_{t-1}^2}{\sigma_{t-1}^2+\frac{1}{s}}$<1, where σ_{t-1}^2 is the variance of the board's posterior beliefs last period and $\frac{1}{s}$ is the variance of the ability shock. Thus, if the shock to ability doubles the variance of the board's beliefs $\left(\sigma_{t-1}^2 = \frac{1}{s}\right)$, the signal from the current period receives twice the weight of the signal from last period.

2. The larger the shocks to ability, the more sensitive the board's beliefs remain to current performance as tenure increases.

Without shocks to ability, as tenure increases, the board's beliefs about the CEO become more precise, and the sensitivity of these beliefs to new performance signals declines. With shocks to ability, the variance of the board's beliefs declines more slowly, if at all, and the beliefs remain more sensitive to new performance signals. Empirically, the degree to which the sensitivity of beliefs to performance declines with tenure indicates the degree to which these beliefs are becoming more precise. If the sensitivity does not decline with tenure, then boards' beliefs are not converging.

1.3 Estimating Bayesian learning models of CEO turnover

To estimate Bayesian learning models of CEO turnover, one needs to add a mean-zero noise term to the (so far) deterministic relationship between prior performance and the board's estimate of CEO ability. Consider, for example, a sample of CEOs in tenure year *t=2* with information on performance in years t=1 and t=2 and a variable *fire* equal to one for CEOs dismissed in year 2:

$$\hat{\alpha}_2 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \vartheta_2 \tag{4}$$

$$fire = 1\ if\ \hat{\alpha}_2 < \underline{\alpha}_2 \tag{5}$$

If the noise term ϑ_2 is normally distributed, this model can be estimated with a probit regression of CEO turnover in year 2 on firm performance in years t=1 and t=2. The latent variable in the probit model is the board's posterior estimate of CEO ability, $\hat{\alpha}_2$, and the probit coefficients correctly estimate the weights the board assigns to prior performance when assessing CEO ability:

$$P(fire = 1) = P(\hat{\alpha}_2 < \underline{\alpha}_2)$$

$$= P\left(\epsilon_2 < \underline{\alpha}_2 - \beta_1 - \beta_1 x_1 - \beta_2 x_2\right) \quad (6)$$

$$= \Phi(\beta_0' - \beta_1 x_1 - \beta_2 x_2) \qquad (with\ \beta_0' = \underline{\alpha}_2 - \beta_1)$$

Estimating (6) with maximum likelihood yields consistent estimates of the weights on prior performance, both for the case with constant CEO ability in equation (2) and for the case with time-varying ability in equation (A.3) in Appendix A.

2 Performance-induced turnover

Estimating models of CEO dismissals, such as the models in the previous section, requires distinguishing firings from other CEO departures. In reality, CEO turnovers occur for many reasons: Some CEOs are dismissed for poor performance, while other CEOs are fired for other reasons, such as personal scandals or violations of rules or laws. Many CEOs depart voluntarily, and these departures can be either related or unrelated to performance (e.g., accepting a more attractive position elsewhere vs. retiring for health reasons). Unfortunately, firms are not required to reveal the true reason for a CEO departure, and might be less likely to do so if a CEO is fired.[9]

To address this problem, the prior literature tries to distinguish forced from voluntary departures by using information on CEO age, the timing of turnover announcements, whether the departing CEO remains on the board, and press reports (see, for example, Warner, Watts, and Wruck (1988), Dennis and Dennis (1995), Kim (1996), and Parrino (1997)). Inevitably, any algorithm that relies on incomplete and often misleading information misclassifies some turnovers. Moreover, CEO departures can be forced without being due to bad performance, and departures can be due to bad performance without being forced. For example, a well-performing CEO might be forced out because of a personal scandal, or bad performance might cause a CEO to voluntarily retire early.

The approach taken in this paper is to do away with any a-priori distinction between forced and voluntary turnover, and instead simply ask whether bad firm performance leads to CEO-firm separations. What matters for future firm performance is whether bad CEO-firm matches are dissolved; whether this dissolution involves a CEO firing, a voluntary retirement, or

[9] See Warner, Watts, and Wruck (1988) and Weisbach (1988) for more detail. Schwartz-Ziv and Weisbach (2013) use private data on minutes of board meetings to document cases in which CEOs are forced out of their jobs that could not be identified using publicly available information.

anything between these two extremes is of secondary importance.[10] To operationalize this idea, we introduce the concept of *performance-induced turnover*, defined as turnover that would not have occurred had performance been "good". It includes all departures caused by bad performance, independently of whether the decision is made by the board (as in the models in Sections 1.1 and 1.2) or by the CEO.

Conceptually, we think of the CEO turnover probability as the sum of two independent turnover processes, one of which is unrelated to firm performance, given by x_t, and one of which is negatively related to performance.

$$P_{turn}(x_t) = P_{other} + P_{perf.-ind.}(x_t) - P_{other} \cdot P_{perf.-ind.}(x_t) \quad (7)$$

The last term is an adjustment for CEOs that experience both performance-induced turnover and other, not performance-related turnover in the same year.[11]

We are interested in estimating the process for performance-induced turnover. Reordering equation (7) yields

$$P_{perf.-ind.}(x_t) = \frac{P_{turn}(x_t) - P_{other}}{1 - P_{other}} \quad (8)$$

Performance-induced turnovers are the difference between all turnovers and those turnovers that are unrelated to performance (and thus occur at any level of performance), with some turnovers caused by both processes. The challenge in estimating equation (8) is finding an estimate of P_{other}, the probability of turnovers not related to performance.

We use two approaches to estimate performance-induced turnovers. The two approaches, presented in Sections 2.1 and 2.2, respectively, make different assumptions about P_{other}, the probability of turnovers unrelated to performance. Because both approaches have advantages and disadvantages, we present results from both in the empirical section.

[10] This idea is explicit in models of the competitive assignment of workers or executives to firms, such as Sattinger (1979) and Eisfeldt and Kuhnen (2013): A CEO-firm match dissolves when the value generated by the match falls below the firm's and the CEO's combined outside options, and for many separations the distinction between quits and firings is not meaningful.
[11] For example, a CEO aged 65 might have retired independently of performance but, if performance was also bad, would have been fired had he not retired.

2.1 A probit model with performance decile indicators

The first approach assumes that the probability of performance-induced turnover is zero at and above some high performance threshold $\hat{X}$, such as the 90th percentile of the performance distribution. All turnovers above $\hat{X}$ are assumed to be unrelated to performance and, thus, to would have occurred at any level of performance.[12] The rate of turnover at and above $\hat{X}$ therefore forms the empirical estimate of P_{other}. Any *higher* turnover probability observed at performance levels below $\hat{X}$ is assumed to be caused by performance being worse. These additional turnovers yield the empirical estimate of $P_{perf-ind}$.

Formally, the probability of performance-induced turnover at performance level x_t (for $x_t < \hat{X}$) is calculated from the difference between the turnover probability at x_t and the average turnover probability at and above the performance threshold $\hat{X}$:[13]

$$P_{perf-ind}\left(x_t, \hat{X}\right) = \frac{Max\left(P_{turn}\left(x_t\right) - P_{turn}\left(x \geq \hat{X}\right), 0\right)}{1 - P_{turn}\left(x \geq \hat{X}\right)} \tag{9}$$

To estimate $P_{perf-ind}(x_t, \hat{X})$ from eq. (9), it is important to choose the right functional form for $P_{turn}(x_t)$, the relation between total turnover and performance. It is especially important that the functional form matches the empirical turnover probability at high levels of performance and, thus, delivers a reliable estimate of $P_{other} = P_{turn}(x \geq \hat{X})$. A standard probit model with linear performance terms, such as that in eq. (6), is not appropriate – it implies that the total turnover probability (and therefore also P_{other}) goes to zero at high levels of performance. If, as seems inevitable, there are turnovers that occur at all levels of performance, a probit model with linear performance does not fit the data.

To allow the turnover probability to converge to a non-zero level at high levels of performance, we model $P_{turn}(x_t)$ as a probit with performance-decile indicators:

$$P_{turn}(x_t) = \Phi(\beta_1 + \beta_2 \cdot Dec_2 + \cdots + \beta_{10} \cdot Dec_{10} + \gamma' \cdot Z_t) \tag{10}$$

[12] A violation of this assumption would lead us to underestimate the frequency of performance-induced turnover. See Section 2.4 for further discussion.

[13] The numerator is set to zero if this difference is negative. As long as the estimated turnover-performance relationship is monotonically downward sloping, this never happens for $x_t < \hat{X}$. The denominator is once again an adjustment for CEOs that experience both performance-induced turnover and other, not performance-related turnover in the same year.

Dec_2 to Dec_{10} are indicators for performance deciles and Z_t is a vector of controls. This specification allows the estimation to match the empirical turnover probability in each performance decile. The probability of turnover unrelated to performance, P_{other}, is calculated as the implied turnover probability with performance in the top decile $P_{turn}(x \geq \hat{X}_{90th\_percentile})$. Given this estimate, the probability of performance-induced turnover is calculated from equation (9).

This approach is straightforward and close to the models used in the prior literature, but it has two disadvantages: First, the need to create decile indicators restricts the model to a single performance measure. If boards use more than one performance measure or assign unequal weights to performance at different lags, this model could not accommodate it. Second, the coefficients estimated from eq. (10) do not correspond to the coefficients in the learning models in Section 1 and, hence, cannot be used to test predictions from these models.

2.2 A two-probit model

The second approach to modeling the turnover-performance relationship explicitly allows for two independent turnover processes, one that is affected by performance and one that is not. We use probit specifications for both processes:

$$
\begin{aligned}
P_{turn}(X_t) &= P_{other} + P_{perf-ind}(x_t) - P_{other} \cdot P_{perf-ind}(x_t) \\
&= P_{other} + (1 - P_{other}) \cdot P_{perf-ind}(x_t) \qquad (11) \\
&= \Phi_{other}(\alpha_1 + \alpha_2 \cdot Z_{1t}) + \left(1 - \Phi_{other}(\alpha_1 + \alpha_2 \cdot Z_{1t})\right)\Phi_{perf-ind}(\beta_1 + \beta_2 \cdot X_t + \gamma' \cdot Z_{2t})
\end{aligned}
$$

X_t is a vector of performance measures, Z_{1t} and Z_{2t} are vectors of controls, and both Φ_{other} and $\Phi_{perf-ind}$ are standard-normal CDFs. Because there are two turnover processes, one of which is not a function of performance, the total turnover frequency can decline with X_t without converging to zero at high performance levels. This two-probit model has the added advantage that it can accommodate multiple performance measures, including multiple lags of performance. Moreover, the coefficients on the performance term(s) X_t correspond to the coefficients in the Bayesian learnings models in Section 1, and, hence, can be used to test predictions from these models. The drawback of this approach is that it requires identifying two independent turnover processes from the data. We discuss the challenges of the estimation below.

2.3 A numerical example

We illustrate both approaches using a simple numerical example with two types of departures: performance-induced departures and departures unrelated to performance, labeled again as "other". In any year, a firm-CEO match may survive or may dissolve because of the performance-induced turnover process (e.g., through a dismissal by the board), because of the "other" turnover process (e.g., a retirement unrelated to performance), or because of both processes simultaneously. The econometrician cannot distinguish the two types of departures but can observe whether a turnover has occurred:

$$P_{turn}(x_t) = P_{other} + P_{perf-ind}(x_t) - P_{other} \cdot P_{perf-ind}(x_t) \tag{12}$$

Performance-induced turnovers are negatively related to firm performance x_t, and the noise terms in both processes follow a standard normal distribution. Specifically, performance-induced departures occur with probability $P_{perf-ind} = \Phi(\beta_1 + \beta_2 \cdot x_t)$, with $\beta_2 < 0$, and "other" departures occur with constant probability $P_{other} = \Phi(\alpha_1)$. The parameters α_1, β_1, and β_2 are set to -1.4, -1.6, and -0.4, respectively, to approximate the empirical turnover probabilities from Section 4. The performance measure x_t is normally distributed with a mean of 0.1 and a standard deviation of 0.3 (to match the empirical section, performance is scaled by its standard deviation).

Figure 2 shows the realized probabilities of total, performance-induced, and "other" turnovers by performance decile in a large simulated sample of *n* = 1,000,000. The probabilities are averaged within each performance decile. The figure also shows estimates of performance-induced turnover probabilities obtained using our two estimation methods. For the probit model with performance deciles, the threshold $\hat{X}$ is set to the 90th percentile, so that all turnovers in the top performance decile are assumed to be "other" turnover.

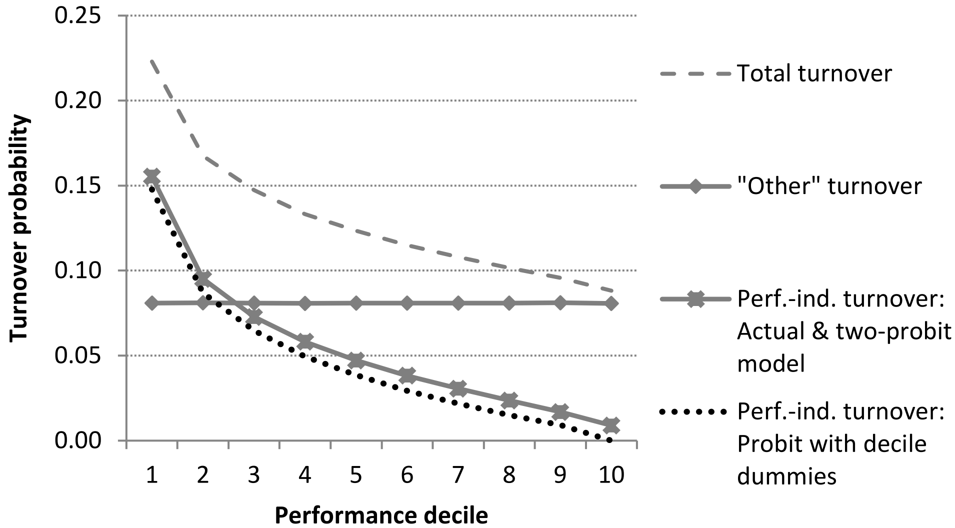

Fig. 2: Estimating performance-induced turnover: numerical example. The simulated sample has 1,000,000 CEO-years. Performance-induced departures occur with probability $P_{perf-ind} = \Phi(\beta_1 + \beta_2 \cdot x_t)$ and other departures occur with probability $P_{other} = \Phi(\alpha_1)$. Parameters α_1, β_1, and β_2 are set to -1.4, -1.6, and -0.4, respectively; x_t is normally distributed with mean 0.1 and standard deviation 0.3. Total turnover is governed by eq. (12). The turnover-performance relation $P_{turn}(x_t)$ is estimated using a standard probit model with decile dummies (eq. (10)) or the two-probit model (eq. (11)), with the performance term x_t scaled by its standard deviation. Performance-induced turnover probabilities are calculated using the probit model with decile dummies and eq. (9), with $\hat{X}$ equal to the 90th percentile of performance, or using the $P_{perf-ind}(x_t)$ term in the two-probit model (eq. (11)). All probabilities shown are averages across observations within each performance decile.

Both estimation methods – probit with decile dummies and two-probit model – closely match the simulated probabilities of performance-induced turnover and their relation to firm performance. In this large sample, the two-probit estimates of performance-induced turnover are virtually indistinguishable from the population probabilities. The estimates from the probit with performance deciles, on the other hand, are consistently slightly lower than the population probabilities. This estimation method makes the overly conservative assumption that none of the turnovers above the 90th performance percentile are performance induced. In this simulation, the true probability of performance-induced turnover in the top performance decile is still 0.9% per year. Hence, by attributing all turnovers in the top performance decile to "other" turnovers, this approach overestimates the rate of "other" and underestimates the rate of performance-induced turnover across all performance deciles.

To assess the behavior of the two estimation methods in samples sized like the empirical data, we repeat the estimations in 500 simulations of 23,000 observations each. Table 1 shows summary statistics for the simulated and the estimated performance-induced turnover probabilities. The results are consistent with those from the large sample: Across all performance deciles, the two-probit model closely replicates the simulated performance-induced turnover probabilities, while the probit model with performance deciles is too conservative and slightly underestimates them.

The bottom panel of Table 1 shows summary statistics for the estimated firm performance coefficients in the two-probit models. Both the mean and median estimates are close to the population coefficient of $\beta_2 =$ -0.40, with a moderate standard deviation of 0.05. Hence, the two-probit estimation can be used to recover structural parameters of the underlying model from the data.

2.4 Discussion

The concept of performance-induced turnover and its empirical counterpart $P_{perf-ind}(x_t)$ offer a new way to analyze the relationship between firm performance and CEO departures. Conceptually, performance-induced turnover differs from *forced* turnover in that it includes any type of departure caused by bad performance, independently of whether the decision is made by the board or the CEO himself. This includes firings by the board, but also cases in which bad performance causes CEOs to give up voluntarily or to retire early. On the other hand, forced turnovers that are unrelated to performance, for example those caused by personal scandals or violations of rules, do not qualify as performance induced.

Performance-induced turnover is, arguably, more relevant for the efficient allocation of managerial talent to firms than forced turnover. What matters for firm performance is whether bad CEO-firm matches are dissolved; whether this dissolution involves a firing, a voluntary retirement, or anything between these two extremes is of secondary importance. A practical advantage of examining performance-induced turnover is that the estimation does not require the researcher to a priori distinguish forced from voluntary turnovers or determine which turnovers are due to bad performance. This avoids the inevitable misclassifications that bias estimates of the frequency and performance-sensitivity of forced turnovers.

There are several caveats. Performance-induced turnover is identified from two features of the data: The rate of turnover at high levels of performance, which informs the estimate of “other” turnover, and the increase in turnover as performance declines. This increase, combined with the estimate for “other” turnover, determines the estimate of performance-induced turnover. The need to estimate two turnover processes from one observed turnover-performance relationship requires assumptions that affect the estimates.

Estimating performance-induced turnover using a standard probit model with performance-decile indicators requires choosing a performance threshold $\hat{X}$ above which all turnovers are assumed to be independent of performance. This assumption is violated if there are turnovers caused by bad performance even above $\hat{X}$ (i.e., turnovers that would not have happened had performance been even better). It is also violated if there are turnovers above the threshold that are caused by *good* performance (i.e., turnover that would not have happened had performance been lower). An example are successful CEOs who are hired away by other firms.[14] Both violations cause us to overestimate the number of "other" turnovers above $\hat{X}$ and to underestimate the number of turnovers caused by bad performance below $\hat{X}$.

This downward bias in the performance-induced turnover estimate might be reduced by increasing $\hat{X}$, which should lower the number of turnovers above $\hat{X}$ that are still due to bad performance. However, the higher $\hat{X}$, the smaller the sample above the threshold from which the rate of "other" turnover is estimated, which increases the noise in the estimate. In robustness tests, we find that estimates of performance-induced turnover are robust to varying $\hat{X}$ between the 85th and 95th percentile of the performance distribution. The turnover-performance relation flattens out at high levels of performance, which supports the assumption that most turnovers in this region are unrelated to performance, and which also makes the exact choice of $\hat{X}$ less important.

The two-probit approach avoids the need to choose an ad-hoc threshold but requires the explicit estimation of two turnover processes – P_{other} and $P_{perf-ind}(x_t)$ – from the observed turnover-performance relationship. The two processes are separately identified from the assumption that one of the processes varies with performance, while the other one does not. Intuitively, the estimation uses the $P_{perf-ind}(x_t)$ process to match the turnover-performance slope and the P_{other} process to match the level of turnover at high levels of performance. This works well if the sample is sufficiently large, such as in the simulations in Table 1 and in the full-sample analysis in Section 4. In smaller samples, however, the estimates can become unstable and highly sensitive to the relatively small number of turnovers at high levels of

[14] Cziraki and Jenter (2017) show that incumbent CEOs are rarely hired away by other firms, which suggests that these events are unlikely to have large effects on our estimates.

performance. Because both estimation methods have advantages and disadvantages, we show estimates from both methods below.

Finally, because performance-induced turnover includes all departures caused by bad performance, independently of whether the decision is made by the board or the CEO, performance-induced turnover is broader than the CEO firings modeled in the Bayesian learning models in Section 1. For example, CEOs who give up because of bad performance play no role in these models but are included in performance-induced turnover. This distinction should be kept in mind when interpreting any differences between the models' predictions and the empirical properties of performance-induced turnover.

3 Sample and data

The construction of the CEO turnover sample starts with all firms in the Standard & Poors ExecuComp database from 1993 through 2011. The database lists top executives in firms included in the S&P 500, S&P MidCap, and S&P SmallCap indices at any time since 1992. We record a CEO turnover whenever the CEO identified in ExecuComp changes. Using news searches in the Factiva database, each turnover is verified and mistakes corrected. The resulting sample has 6,272 CEO spells in 3,152 firms, with 31,541 CEO-years and 3,472 turnovers. Merging with control variables reduces the sample to 4,942 CEO spells in 2,977 firms, with 23,399 CEO-years and 2,727 turnovers. Table 2 shows descriptive statistics for the final sample.

All CEO turnovers in the panel from 1993 to 2010 are classified as either voluntary or forced using the Parrino (1997) algorithm. Section 4.3 and Appendix B describe details of the classification procedure. The required turnover announcements, press reports, and CEO ages are obtained by searching the Factiva database. For the years 2002 to 2010, we combine our own data collection with data from Peters and Wagner (2014). This procedure yields 823 forced and 2,424 voluntary turnovers in 27,645 CEO-years. Merging with control variables reduces the sample to 735 forced and 2,010 voluntary turnovers in 20,435 CEO-years.

Financial statement data is from the Compustat database and stock return data from the Center for Research in Security Prices (CRSP). The measure of firm performance used in the CEO turnover regressions is average monthly stock returns scaled by their standard deviation. The standard deviation is measured over 48 months, ending with and including the period over which stock returns are averaged. The reason for normalizing stock returns by their standard deviation is to make the returns of more and less volatile firms comparable.[15]

4 Empirical analysis

This section presents empirical estimates of performance-induced turnover. The analysis uses the two estimation approaches described earlier: the standard probit with performance decile indicators and the two-probit model. Section 4.1 presents the main results. Section 4.2 compares performance-induced to forced turnover. Section 4.3 examines how much performance history boards use in turnover decisions, while Sections 4.4 and 4.5 explore how performance-induced and forced turnover change with CEO tenure. Section 4.6 explores whether and how performance-induced turnover has changed over the sample period.

4.1 Performance-induced turnover

This section presents estimates of performance-induced turnover using the full sample. The dependent variable is set to one for tenure years with any type of CEO turnover and to zero otherwise. Results from standard probit models with performance-decile indicators are in Table 3. The key independent variables are decile indicators for the firm's past stock price performance. Performance is measured as average monthly stock returns scaled by their standard deviation. Because it is not a priori known how long a performance history boards consider when assessing CEOs, we show results for four different performance periods. In the first three regressions, returns are measured from tenure year -1, -2, or -3 through year zero (the turnover year), respectively. The fourth regression measures performance over the CEO's entire tenure up to (and including) year zero. All regressions control for firm size, an indicator for dividend payers, CEO age, and tenure.[16]

The coefficient estimates in Panel A confirm that CEO turnover decreases as firm performance increases. The model-implied turnover probabilities are reported in Panel B. Using equation (9), the probability of performance-induced turnover is calculated for each observation from the difference between the model-implied total turnover probability and what this probability would have been had performance been in the top decile. In the language of

[15] All results are qualitatively unchanged without this normalization.
[16] Including ROA and market-to-book as additional controls strengthens the results or leaves them unchanged. Because these controls capture aspects of firm performance, they complicate the interpretation of the results.

Section 2.1, P_{other} is estimated as $P_{turn}(x \geq \hat{X}_{90th\_percentile})$, and performance-induced turnover at performance level x_t is derived from the additional turnover probability the model attributes to performance being worse than $\hat{X}$.

The implied probabilities in Panel B reveal the importance of performance-induced turnover. Total turnover probabilities rise from around 8% per year for the top performance decile to around 18% for the bottom decile. Performance-induced turnover probabilities are (by construction) 0% in the top decile but increase to around 12% in the bottom decile, averaging between 4.0 and 4.4% per year if performance is measured over two to four years. Lengthening the performance window first increases and then decreases the probability of performance-induced turnover; extending it to the full CEO tenure lowers the estimate to 3.4%.[17] Measuring performance over three years yields the steepest turnover-performance slope and a performance-induced turnover probability of 4.4% per year (column (2)). Compared to a total turnover rate of 11.7%, this suggests that 38% of all turnovers are performance induced.

Results from two-probit models are in Table 4. Panel A reports coefficient estimates for both probit terms. The performance measures are included only in the first probit, which delivers our estimate of performance-induced turnover. The second probit, which delivers our estimate of "other" turnover, includes three indicators for retirement age (61-63, 64-66, and 66+). The control variables are the same in both terms, matching those in the standard probit in Table 3.

As expected, performance-induced turnover decreases in firm performance, while "other" turnover increases in CEO age and peaks around age 64-66. The model-implied turnover probabilities are in Panel B. The two-probit model yields higher estimates of performance-induced turnover than the standard probit. Measuring performance again over three years (column (1)), the performance-induced turnover rate is 2.1% at the 95th performance percentile, rises to 13.3% at the 5th percentile, and averages 6.4% per year (or 55% of all turnovers). Across the different specifications, the performance-induced turnover rate varies between 6.1% and 7.2% per year, which makes 52% to 57% of all turnovers performance induced.

[17] We examine the effects of performance at different lags more carefully in Section 4.3.

Figure 3 depicts actual and model-implied CEO turnover rates as a function of performance. Figure 3.a shows estimates from the probit with decile indicators and Figure 3.b from the two-probit model, with performance again measured over three years. Both models match the empirical turnover-performance relationship closely. However, the two models diverge on how the overall turnover rate is split between performance-induced and "other" turnover.

It is no surprise that the two-probit model delivers higher estimates of performance-induced turnover than the probit with performance-decile indicators. The probit with decile indicators makes the ad-hoc assumption that there are no performance-induced turnovers above the 90th percentile of the performance distribution. Any violation of this assumption causes a downward bias in the estimate of performance-induced turnover (as illustrated in the simulations in Section 2.3). Hence, the estimates from the probit with decile indicators are likely to understate the actual rate of performance-induced turnover.

The two-probit model instead *estimates* how much performance-induced turnover there still is at high levels of performance, assuming that its frequency smoothly declines to zero as performance increases. According to our two-probit estimates, the rate of performance-induced turnover at the 95th performance percentile is still 2.1% per year, substantially higher than zero. Intuitively, the two-probit model uses the turnover-performance slope at high levels of performance to deduce how much performance-induced turnover there still is.[18] While much less restrictive, its sensitivity to the turnover-performance slope at high levels of performance makes the two-probit model more difficult to estimate in small samples.

4.2 Performance-induced vs. forced turnover

Despite their differences, the estimates from both approaches show that performance has a larger effect on CEO turnover than suggested by the prior literature. Most prior studies focus on forced CEO turnovers, which are identified using press releases, news reports, announcement dates, and CEO ages. Typical studies classify between 13 and 21% of turnovers as forced.[19] Hence, our estimates in the previous section suggest that there are substantially

[18] A flat turnover-performance slope at high performance levels indicates few performance-induced turnovers, while a steep slope indicates that performance-induced turnover still plays an important role.
[19] Using different algorithms, the percentage of CEO turnovers classified as forced is 20% in Warner, Watts, and Wruck (1988), 18% in Dennis and Dennis (1995), 13% in Parrino (1997), 13% in Huson, Parrino, and Starks (2001), 19% in Parrino, Sias, and Starks (2003), 16% in Huson, Malatesta, and Parrino (2004), 13%

more performance-induced than "forced" turnovers. This is all the more surprising given that forced turnovers include CEO dismissals unrelated to firm performance, such as firings for personal scandals.

Because firms are not required to reveal the true reasons for CEO departures, prior studies use a variety of algorithms to sort turnovers into those that are forced and those that are voluntary. The most widely used algorithm was introduced by Parrino (1997) and uses press reports, the time between the turnover announcement and the actual turnover, and the CEO's age at departure to classify turnovers as either forced or voluntary.[20] Appendix B gives a detailed description of the steps involved in the classification. Applying the Parrino algorithm to our CEO panel for the 1992 – 2010 period yields 879 forced and 2,395 voluntary turnovers in 27,708 tenure years.

We use this classification to estimate standard forced turnover probit regressions. The dependent variable equals one for tenure years with a forced turnover and zero otherwise. The control variables and performance measurements are the same as in the previous section. Consistent with prior studies, forced turnover is strongly related to firm performance (Table 5, Panel A). However, both the level of forced turnover and its increase as performance worsens are smaller than for performance-induced turnover (Panel B). The rate of forced turnover is 2.8% per year, substantially smaller than the 4.4% performance-induced turnover rate from the probit with decile dummies (Table 3) or the 6.4% rate from the two-probit model (Table 4). If we again assume that boards consider three years of performance (column (1)), the probability of forced turnover rises to 7.3% at the 5th performance percentile, much below the 12.2 to 13.3% for performance-induced turnover in Tables 3 and 4.

The reason for the larger number of performance-induced than forced turnovers is simple: Turnovers classified as "voluntary" by the Parrino algorithm are significantly more frequent at lower levels of performance, suggesting that many of them are in fact performance induced. This is evident in Table 6, which presents regressions of an indicator for voluntary turnover on

in Engel, Hayes, and Wang (2003), 17% in Clayton, Hartzell, and Rosenberg (2005), 18% in Fich and Shivdasani (2006), 19% in Brookman and Thistle (2009), 17% in Taylor (2010), 21% in Hazarika, Karpoff, and Nahata (2012), 20% in Helwege, Intintoli, and Zhang (2012), and 21% in Mobbs (2013).

[20] The Parrino algorithm has been used by, among others, Parrino (1997), Farrell and Whidbee (2000, 2003), Huson, Parrino, and Starks (2001), Parrino, Sias, and Starks (2003), Huson, Malatesta, and Parrino (2004), Fich and Shivdasani (2006), Yermack (2006), Lel and Miller (2008), Brookman and Thistle (2009), Bushman, Dai, and Wang (2010), Taylor (2010), Hazarika, Karpoff, and Nahata (2012), Kaplan and Minton (2012), Mobbs (2013), Peters and Wagner (2014), Guo and Masulis (2015), and Jenter and Kanaan (2015).

firm performance and the same control variables as in Table 5. Voluntary turnover is highly significantly related to firm performance (Panel A). Assuming again that boards consider three years of performance, the model-implied probability of a voluntary turnover increases from 7.6% at the 95th performance percentile to 11.9% at the 5th percentile (Panel B).[21] Because the prior literature focuses on forced turnovers and ignores this increase, it underestimates the number of turnovers caused by bad performance.

The difference between performance-induced and forced turnovers is largest for retirement-age CEOs. Almost all classification algorithms, including the Parrino algorithm, assume that turnovers at or above typical retirement ages are likely to be voluntary. In the data, however, even turnovers of retirement-age CEOs are significantly more likely when performance is low. This is illustrated in Figure 1.b in the introduction, which shows turnover rates for CEOs aged 60 and higher: Based on the Parrino algorithm, there are almost no forced turnovers in this age group. The substantial increase in turnovers as performance declines is therefore attributed to "voluntary" departures, which in this age group turn out to be more performance-sensitive than forced ones. Our approach instead attributes the same increase to performance-induced turnovers.

4.3 How much performance history do boards use?

The Bayesian learning model with constant CEO ability (see Section 1.1) predicts that boards assign the same weight to all lags of the performance signal. Intuitively, because CEO ability and the relationship between ability and performance are constant, performance one year ago contains as much information about CEO ability as performance ten years ago. To test this prediction, we include separate performance terms for the current tenure year, the previous tenure year, etc., in CEO turnover regressions. Both the two-probit model for performance-induced turnover (Table 4) and standard forced turnover regressions (Table 5) can accommodate multiple lags of performance.[22]

The Bayesian learning model with constant CEO ability is strongly rejected by the estimates in Tables 4 and 5. In the two-probit model (Table 4), boards assign significantly

[21] Figure 1.a in the introduction illustrates the same result using raw data instead of model-implied numbers: As performance declines, the probability of a voluntary turnover rises from 6.8% above the 95th performance percentile to 13.7% below the 5th percentile.
[22] The need to create indicator variables restricts the "probit with decile indicators" approach to estimating performance-induced turnover to a single performance measure.

higher weight to recent performance in tenure years 0 and -1 than to performance in previous years. In column 3, which includes four years of performance, the coefficient on performance declines from -0.21 for tenure year -1 to -0.13 and -0.06 for tenure years -2 and -3, respectively. Wald tests show these differences to be statistically significant, with chi-squared statistics of 7.02 (p=0.01), 18.47 (p=0.00), and 6.36 (p=0.01) for comparisons between years -1 and -2, -1 and -3, and -2 and -3, respectively.[23] Including an additional performance term for tenure year -4 in column (4) yields an insignificant coefficient of -0.01.

Similar to performance-induced turnovers, forced turnovers are also much more closely linked to recent performance than to performance in the more distant past (Table 5). In column (3) of Table 5, which again includes four years of performance, the coefficient on performance declines from -0.29 for tenure year -1 to -0.13 and -0.08 for tenure years -2 and -3, respectively. Using Wald tests, the chi-squared statistics for these differences are 27.3 (p=0.00), 43.11 (p=0.00), and 2.54 (p=0.11) for years -1 and -2, -1 and -3, and -2 and -3, respectively. This consistent pattern of declining coefficients on lagged performance in Tables 4 and 5 suggests that the Bayesian learning model with constant CEO ability is a bad fit for both forced and performance-induced turnovers.

One potential explanation for boards assigning higher weight to more recent performance is that CEO ability, or the quality of the CEO-firm match, changes over time (see Section 1.2). The rapid decline of the coefficients on lagged performance in Tables 4 and 5 suggests that the necessary shocks to CEO ability are large. Based on the two-probit estimates, performance three years ago receives only about one-third of the weight of performance one year ago, and performance from four or more years ago is mostly ignored. In the context of the Bayesian learning model in Section 1.2, this implies that CEO ability (or match quality) changes so rapidly that performance from four years ago is almost completely uninformative about CEO ability today.

The results in Tables 4 and 5 also suggest that turnover regressions that use only one performance term are misspecified. These regressions implicitly impose the same weight on performance at all lags within the performance window, while in reality boards put more

[23] The coefficients on performance in tenure years 0 and -1 are more difficult to compare but suggest the same pattern. If there is a turnover, some of the year 0 performance occurs before and some after the event. Performance subsequent to a turnover cannot predict the turnover and is likely to lower the coefficient on year 0 performance. Hence, the similarity of the coefficients on performance in year 0 and year -1 suggests that boards assign higher weight to pre-turnover performance in year 0 than to performance in year -1.

weight on more recent performance. For estimating performance-induced turnover, this gives an advantage to the two-probit model, which can accommodate multiple performance terms with different weights, over the probit with decile indicators.

4.4 Performance-induced turnover across tenure

We next explore how performance-induced turnover changes with CEO tenure. The Bayesian learning model with constant CEO ability of Section 1.1 predicts that the performance sensitivity of boards' beliefs about CEO ability declines with tenure. As boards' beliefs become more precise, each performance signal affects these beliefs less. Consequently, the coefficients on performance in turnover regressions shrink as tenure increases. To test this prediction, we estimate a two-probit model, similar to that in Table 4, column 3, and interact each performance term with dummies for seven tenure periods: tenure years 1-2, 3-4, 5-6, 7-8, 9-11, 12-16, and 17 or higher. The estimates are reported in Table 7.

There are three important results. First, the coefficients on firm performance show little to no decline with CEO tenure, at least for the first ten years. Most of the coefficients on contemporaneous and lagged firm performance are in fact larger in tenure years 7-11 than in tenure years 2-4. There is some evidence that the coefficients decline after tenure year 11, but the estimates are imprecise – e.g., the coefficient on t=-1 performance is actually larger in tenure years 17+ than in tenure year 2. Hence, there is little support for the prediction that the coefficients on performance decline with tenure because boards' beliefs about CEOs become more precise. The results instead suggest that boards are unable to figure out CEO ability for at least the first ten years of tenure.

Second, for CEOs of all tenure levels, recent performance has a much stronger effect on turnover than performance in the more distant past. This confirms the full-sample results of Section 4.3. For example, in tenure years 7-8, the coefficient on performance declines from -0.25 for year -1 to -0.16 for year -2 and -0.12 for year -3. Even in tenure years 12-16, only current performance and performance in the previous two years has statistically significant effects on turnover. These results again reject the learning model with constant CEO ability, according to which all performance lags should affect CEO turnover equally. Instead, boards act as if performance from four and more years ago contains almost no information about CEO ability (or match quality) today.

Third, the frequency of performance-induced turnover declines only slowly as tenure increases. Illustrated in Figure 4.a, the model-implied performance-induced turnover rate is close to 6.5% p.a. throughout tenure years 2-8 (7.0%, 6.2%, 6.6%, 6.2% in years 2, 3-4, 5-6, and 7-8, respectively), and then declines slowly to 5.3% in tenure years 17 and higher. Notably, according to these estimates, 65% of turnovers in the first eight tenure years are performance induced.

The evidence in Table 7 suggests (i) that boards' beliefs about CEO ability remain sensitive to performance even late in tenure, (ii) that boards pay more attention to recent performance than to performance in the more distant past, and (iii) that the rate of performance-induced turnover remains high even late in tenure. This evidence is consistent with a model in which boards' learning is hampered by shocks to CEO ability. With changing CEO ability, boards optimally assign larger weights to more recent performance signals than to older ones. With changing CEO ability, the variances of boards' beliefs about CEOs also decline more slowly, if at all, and the beliefs remain sensitive to new performance signals even late in tenure (see Section 1.2).

The shocks to CEO ability that reconcile the Bayesian learning model with the data would need to be large. To keep the variance of boards' beliefs, and the sensitivity of those beliefs to new performance signals, constant over time, the shocks to CEO ability have to offset the boards' learning from new performance signals. The large sensitivity of turnover to current performance shows that current performance is informative about CEO ability even late in tenure, yet shocks to ability are apparently large enough to reverse any gains in the precision of boards' beliefs.

4.5 Forced turnover across tenure

The prior section's conclusions are not an artifact of focusing on performance-induced turnover: Repeating the tenure analysis with forced turnovers in Table 8 yields similar results. The coefficients on recent performance barely decline as tenure increases, suggesting again that boards' beliefs about CEO ability are not converging. Moreover, for CEOs of all tenure lengths, recent performance tends to have a much a stronger effect on forced turnover than performance in the more distant past.

There is one notable difference between forced and performance-induced turnovers: Forced turnovers decline more rapidly as tenure increases. Illustrated in Figure 4.b, the implied probability of a forced CEO turnover is 4.6% per year in tenure year 2, 3.3% in years 7-8, and 1.0% in tenure years 17 and higher. This 78% decline far exceeds the corresponding 25% decline of performance-induced turnover over the same tenure span (see Figure 4.a).

The prior literature has interpreted the decline in forced turnover over tenure as evidence of increasing CEO entrenchment. Our results suggest instead that a large part of this decline is simply a consequence of the forced turnover classification algorithms: Tenure and age are highly correlated, and almost all algorithms assume that turnovers at or above typical retirement ages are likely to be voluntary. This causes a mechanical decline in forced turnovers as tenure increases and more CEOs reach retirement age. Our evidence shows, however, that even turnovers of long-tenured CEOs, many of which are of retirement age, are significantly more likely when performance is low.

4.6 Changes in performance-induced turnover over time

Huson, Parrino, and Starks (2001) and Kaplan and Minton (2011) report that both overall and forced CEO turnover rates have been increasing since the 1970s.[24] To examine whether and how performance-induced turnover has changed during our sample period, we estimate the two-probit model separately for 1993-1999, 2000-2005, and 2006-2011. Each regression includes all performance lags that are statistically significant at the 10 percent level in at least one of the periods. The regression results are in Table 9 Panel A and the implied turnover probabilities in Panel B.

The estimated rate of performance-induced turnover increases from 5.1% per year in 1993-99 to 7.8% in 2000-05, followed by a decline to 6.6% in 2006-11. In parallel, the overall turnover rate increases from 11.6% in 1993-99 to 13.2% in 2000-05, consistent with the results of Kaplan and Minton (2011). However, it falls back again to 11.7% in 2006-11, suggesting that the upward trend in CEO turnover has come to a halt towards the end of the sample. One potential explanation, consistent with the decline in performance-induced turnover, is that boards were less likely to dismiss CEOs for bad performance during the period of the recent financial crisis.

[24] Graham, Kim, and Leary (2017) show that CEO turnover rates were even higher in the 1950s and 60s and declined in the first half of the 1970s.

5 Discussion

5.1 Underestimating performance-induced turnover

There are several reasons to believe that our estimates of performance-induced turnover underestimate the true frequency. First, the actual performance measure(s) used by boards to evaluate CEOs are unknown, and boards have access to performance signals that are unobservable to the econometrician.[25] Using the wrong performance measure implies that we underestimate the effect of (correctly measured) performance on CEO turnover. Specifically, we overestimate the number of turnovers at high levels of performance (and hence the number of turnovers unrelated to performance), and we underestimate the number of turnovers at low levels of performance (and hence the number of performance-induced turnovers).

Second, stock returns are a problematic measure of performance in CEO turnover regressions because stock prices are forward looking – they incorporate investors' assessment of the probability of a CEO turnover. If investors deem a turnover likely, stock prices already reflect in part the expected value of the firm under the successor. This reduces the predictive power of stock prices for CEO turnover and biases the estimates of performance-induced turnover downward.[26]

Finally, estimating performance-induced turnover using a probit model with performance-decile indicators requires a performance threshold above which all turnovers are assumed to be independent of performance. If this assumption is violated, we underestimate the rate of performance-induced turnover. This occurs if there are turnovers caused by bad performance above the performance threshold, i.e., turnovers that would not have occurred had performance been even better. An example are CEOs who retire at, say, the 95% percentile of the performance distribution but would have stayed had performance been at the 99% percentile. This also occurs if there are turnovers above the threshold that are caused by *good* performance, i.e., that would not have happened had performance been lower. An example are successful CEOs who are hired away by other firms. Both violations cause us to overestimate the number

[25] Cornelli, Kominek, and Ljungqvist (2013) provide evidence for the importance of "soft" information in the evaluation and firing of CEOs.
[26] Feedback effects between corporate actions and stock prices have been analyzed by Dow and Gorton (1997), Bond, Goldstein, and Prescott (2010), and Edmans, Goldstein, and Jiang (2012, 2015).

of "other" turnovers, and hence to underestimate the number of turnovers that are due to bad performance.

5.2 Other determinants of CEO turnover

In Section 4, we have compared the empirical properties of performance-induced turnover to predictions from the Bayesian learning models described in Section 1. We concluded that the evidence rejects the model with constant CEO ability (Section 1.1) but is consistent with a model with changing CEO ability (Section 1.2). However, these highly stylized models at best capture some of the factors determining CEO turnover in reality. Our interpretation of the evidence might be incorrect if turnover is determined by factors outside those models. This section offers a brief discussion of other likely determinants of CEO turnover and its evolution with CEO tenure.

5.2.1 Learning-by-doing

Theories of learning-by-doing propose that CEOs build up firm-specific human capital through their on-the-job experience (Garen (1988)). As tenure increases, incumbent CEOs' expected ability improves, on average, relative to that of potential replacements. The main empirical implication is that performance-induced turnovers should decline with tenure.

The empirical result that performance-induced turnover is almost constant in tenure years two to eight and then declines slowly (see Figure 4) does not disprove the importance of learning-by-doing. However, it suggests that other factors, such as slow learning about CEO ability or high turnover costs, offset its effect.

5.2.2 Increasing entrenchment

Theories of increasing entrenchment predict that the cost of dismissing CEOs increases with tenure. This might, for example, be because the CEO is gradually appointing his supporters to the board of directors (Hermalin and Weisbach (1998, 2003)). The main empirical prediction is again that performance-induced turnovers should decline with tenure.

As before, the result that performance-induced turnover is roughly constant until tenure year eight and then declines slowly does not disprove that entrenchment increases. However, it suggests that it takes many years before CEOs are protected against performance-induced turnover.

5.2.3 Heterogeneity and selection

The Bayesian learning models in Section 1 assume that CEOs are heterogeneous in their ability and predict that, as tenure increases, the surviving CEOs are selected for higher ability. However, there are many other dimensions of heterogeneity that these models ignore. For example, CEOs might differ in their level of entrenchment, or firms might differ in their ability to evaluate their CEO. As tenure increases and CEOs are being replaced, the pool of surviving CEOs should be increasingly selected for being entrenched, for working for firms which are unable to evaluate CEOs, and for other factors associated with less turnover.

The main empirical prediction is again that performance-induced turnover should decline with tenure. The results in this paper suggest that these selection effects are initially either weak or offset by other factors.

5.2.4 Incentives

The optimal contracts of some dynamic moral hazard models include CEO dismissals, even though there is no uncertainty about CEO ability.[27] Instead, the threat of termination after poor performance provides CEOs with ex-ante effort incentives. Depending on the parameterization, these models can be consistent with termination threats that increase or decrease with tenure. Moreover, because the purpose of the firing threat is to induce CEO effort, firing based on recent performance can be optimal. Whether a moral hazard model can quantitatively match the observed performance-induced turnover rate, its dependence on recent performance, and its evolution with tenure is an interesting and open question.

6 Summary and conclusion

This paper has introduced the concept of performance-induced turnover, defined as turnover that would not have occurred had performance been "good". Performance-induced turnover is identified from two features of the data: The rate of turnover at high levels of performance, which informs the estimate of "other" turnover unrelated to performance, and the increase in turnover as performance declines. The assumption is that turnovers at sufficiently

[27] See, among others, DeMarzo and Sannikov (2006), DeMarzo and Fishman (2007), Biais, Mariotti, Plantin, and Rochet (2007), Sannikov (2008), He (2012), and the review in Edmans, Gabaix, and Jenter (2017).

high performance levels are unrelated to performance, while any higher turnover rate at lower levels of performance is performance induced.

We find CEO turnover to be closely linked to performance, and performance-induced turnovers to be significantly more frequent than forced turnovers. Depending on the estimation method, we estimate that between 38% and 55% of all CEO turnovers are performance induced, with an even higher percentage in the first years of tenure.

The evidence also shows that boards pay more attention to recent performance than to performance in the more distant past, that boards' beliefs about CEO ability remain sensitive to performance even late in tenure, and that the rate of performance-induced turnover declines only slowly with tenure. All this is consistent with a model in which boards' learning about CEOs is hampered by shocks to CEO ability or to the quality of the CEO-firm match.

Appendix A: A Bayesian learning model with shocks to CEO ability

As in Section 1.1, we assume that the board's initial prior about the CEO's ability α_0 is normally distributed with mean $\hat{\alpha}_0$ and variance $\frac{1}{\tau_0}$. We set $\hat{\alpha}_0 = 0$ for simplicity. CEO ability follows a random walk:

$$\alpha_t = \alpha_{t-1} + \nu_t \quad \text{where } \nu_t \sim \mathrm{N}\left(0, \frac{1}{\mathrm{s}}\right) \tag{A.1}$$

Every period, the board updates its prior about ability based on firm performance x_t:

$$x_t = \alpha_t + \epsilon_t \quad \text{where } \epsilon_t \sim \mathrm{N}\left(0, \frac{1}{\mathrm{r}}\right) \tag{A.2}$$

The random shock ν_t occurs in the beginning of each period *t*, before the board observes the signal x_t. The board then forms its posterior belief $\hat{\alpha}_t$ and fires the CEO if the posterior mean falls below an endogenous threshold $\underline{\alpha}_t$.

Because the board expects ability to change randomly at the start of each period *t*, the variance of the board's prior belief in *t* no longer corresponds to the variance of its posterior belief in *t-1*. The random shock adds to the board's uncertainty about ability and increases the variance of its prior belief in *t* to $\sigma_t^2 + \frac{1}{s}$, compared to simply σ_t^2 without shocks to ability.

The board's posterior beliefs at the end of period *t=1, 2,* and *3* are: [28]

$$\hat{\alpha}_1 = \frac{r}{\left(\sigma_0^2 + \frac{1}{s}\right)^{-1} + r} x_1 \tag{A.3.1}$$

$$\hat{\alpha}_2 = k_{2,1} \frac{r}{\left(\sigma_1^2 + \frac{1}{s}\right)^{-1} + r} x_1 + \frac{r}{\left(\sigma_1^2 + \frac{1}{s}\right)^{-1} + r} x_2 \tag{A.3.2}$$

$$\hat{\alpha}_3 = k_{3,2} k_{3,1} \frac{r}{\left(\sigma_2^2 + \frac{1}{s}\right)^{-1} + r} x_1 + k_{3,1} \frac{r}{\left(\sigma_2^2 + \frac{1}{s}\right)^{-1} + r} x_2 + \frac{r}{\left(\sigma_2^2 + \frac{1}{s}\right)^{-1} + r} x_3 \tag{A.3.3}$$

$$where\ \ k_{t,i} = \frac{\sigma_{t-i}^2}{\sigma_{t-i}^2 + \frac{1}{s}} \tag{A.3.4}$$

The board no longer assigns equal weights to all past signals when forming its beliefs. Signals from the more distant past receive lower weights because they are less informative

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[28] The general expression for the posterior mean in year t is: $\hat{\alpha}_t = \sum_{i=0}^{t} \varphi_{t,i} \frac{r}{\left(\sigma_{t-1}^2 + \frac{1}{s}\right)^{-1} + r} x_{t-i}$, with $\varphi_{t,i} = 1$ for *i=0,* and $\varphi_{t,i} = \prod_{j=1}^{i} k_{t-j}$ with $k_{t-j} = \frac{\sigma_{t-j-1}^2}{\sigma_{t-j-1}^2 + \frac{1}{s}}$ for *i>0.*

about current ability. By how much lagged signals are downgraded depends on how much uncertainty the shocks add to the board's beliefs, which is measured by the $k_{t,i} < 1$ terms.

Consider equation (A.3.2): To form its posterior belief at the end of period $t=2$, the board discounts the once-lagged signal x_1 by $k_{2,1} = \frac{\sigma_1^2}{\sigma_1^2+\frac{1}{s}} < 1$. In the case of constant ability $\left(\frac{1}{s} = 0\right)$, $k_{2,1} = 1$, and both performance signals receive the same weight. If instead the second-period shock to ability doubles the variance of the board's beliefs, $k_{2,1} = \frac{1}{2}$, and x_1 gets half the weight of x_2. If the shocks to ability are so large that x_1 becomes completely uninformative about ability in $t=2$ $\left(\frac{1}{s} = \infty\right)$, $k_{2,1} = 0$, and the board pays attention to only the most recent performance signal.

The board's uncertainty about ability can increase or decrease with tenure. The variance of the board's posterior belief at the end of period t is:

$$\sigma_t^2 = \left(\left(\sigma_{t-1}^2 + \frac{1}{s}\right)^{-1} + r\right)^{-1} \tag{A.4}$$

Whether σ_t^2 is higher or lower than σ_{t-1}^2 depends on the strength of the signal (r) relative to the magnitude of the shock ($\frac{1}{s}$). Empirically, we can infer whether the board's uncertainty decreases or increases with tenure from how the sensitivity to the most recent performance signal changes over time. From equation (A.3), if the board's beliefs become more precise as tenure increases, their sensitivity to the most recent performance signal declines. The speed with which this sensitivity declines indicates the speed with which the board is learning about CEO ability.

Appendix B: The Parrino classification algorithm

The Parrino (1997) algorithm classifies CEO departures as forced or voluntary based on information in departure announcements and press reports. Our implementation of the algorithm consists of three steps. First, all cases in which the press reports that a CEO is forced out, fired, ousted, or leaves due to policy differences or pressure are classified as forced. Second, all cases not classified as forced and with a CEO under the age of 60 are reviewed and reclassified as forced if (1) the stated departure reason is not death, poor health, or acceptance of another position, or (2) the CEO is retiring but does not announce the retirement at least six months before the departure. Third, all cases classified as forced in the previous step are investigated again and reclassified as voluntary if the press convincingly explains that the CEO is leaving for personal or business reasons unrelated to the firm's activities, or if the CEO remains or becomes chairman of the board after the resignation.

References

Biais, Bruno, Thomas Mariotti, Guillaume Plantin, and Jean-Charles Rochet, 2007, Dynamic security design: Convergence to continuous time and asset pricing implications, Review of Economic Studies, 74(2), 345-390.

Bond, Philip, Itay Goldstein, and Edward Simpson Prescott, 2010, Market-based corrective actions, Review of Financial Studies 23(2), 781-820.

Brookman, Jeff, and Paul D. Thistle, 2009, CEO tenure, the risk of termination and firm value, Journal of Corporate Finance 15, 331-344.

Bushman, Robert, Zhonglan Dai, and Xue Wang, 2010, Risk and CEO turnover, Journal of Financial Economics 96, 381-398.

Clayton, Matthew C., Jay C. Hartzell, and Joshua Rosenberg, 2005, The impact of CEO turnover on equity volatility, Journal of Business 78(5), 1779-1808.

Cornelli, Francesca, Zbigniew Kominek and Alexander Ljungqvist, 2013, Monitoring managers: Does it matter?, Journal of Finance 68(2), 431-481.

Coughlan, Anne, and Ronald Schmidt, 1985, Executive compensation, management turnover, and firm performance: An empirical investigation, Journal of Accounting and Economics 7, 43-66.

Cziraki, Peter, and Dirk Jenter, 2017, Hiring CEOs, Working paper, London School of Economics and Political Science and University of Toronto.

DeMarzo, Peter M., and Michael J. Fishman, 2007, Agency and optimal investment dynamics, Review of Financial Studies 20(1), 151-188.

DeMarzo Peter M., and Yuliy Sannikov, 2006. Optimal security design and dynamic capital structure in a continuous-time agency model, Journal of Finance 61(6), 2681-2724.

Denis, David J., and Diane K. Denis, 1995, Performance changes following top management dismissals, Journal of Finance 50(4), 1029-1057.

Denis, David J., Diane K. Denis, and Atulya Sarin, 1997, Ownership structure and top executive turnover, Journal of Financial Economics 45(2), 193-221.

Dikolli, Shane S., William J. Mayew, and Dhananjay Nanda, 2014, CEO tenure and the performance-turnover relation, Review of Accounting Studies 19, 281-327.

Dow, James, and Gary Gorton, 1997, Stock market efficiency and economic efficiency: Is there a connection?, Journal of Finance 52(3), 1087-1129.

Edmans, Alex, Xavier Gabaix, and Dirk Jenter, 2017, Executive compensation: A survey of theory and evidence, forthcoming in: Benjamin Hermalin and Michael Weisbach (eds.), Handbook of the Economics of Corporate Governance, Elsevier Science North Holland .

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, Journal of Finance 67(3), 933-971.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2015, Feedback effects, asymmetric trading, and the limits to arbitrage, American Economic Review 105, 3766-3797.

Eisfeldt, Andrea L., and Camelia M. Kuhnen, 2013, CEO turnover in a competitive assignment framework, Journal of Financial Economics 109, 351-372

Engel, Ellen, Rachel M. Hayes, and Xue Wang, 2003, CEO turnover and properties of accounting information, Journal of Accounting and Economics 36, 197-226.

Farber, Henry S., 1994, The analysis of interfirm worker mobility, Journal of Labor Economics 12(4), 554-593.

Farber, Henry S., 1999, Mobility and stability: The dynamics of job change in labor markets, in: Orley Ashenfelter and David Card (eds.), Handbook of Labor Economics Vol. 3b, Elsevier Science North Holland, Chapter 37: 2439-2483.

Farrell, Kathleen A. and David A. Whidbee, 2000, The consequences of forced CEO succession for outside directors, Journal of Business 73(4), 597-627.

Farrell, Kathleen A. and David A. Whidbee, 2003, Impact of firm performance expectations on CEO turnover and replacement decisions, Journal of Accounting and Economics 36, 165-196.

Fich, Eliezer M., and Anil Shivdasani, 2006, Are busy boards effective monitors?, Journal of Finance, 61(2), 689-724.

Garen, John E., 1988, Empirical studies of the job matching hypothesis, Research in Labor Economics 9, 187-224.

Garret, Daniel F., and Alessandro Pavan, 2012, Managerial turnover in a changing world, Journal of Political Economy 120, 879-925.

Gibbons, Robert, and Kevin J. Murphy, 1992, Optimal incentive contracts in the presence of career concerns: theory and evidence, Journal of Political Economy 100, 468-505.

Graham, John R., Hyunseob Kim, and Mark Leary, 2017, CEO power and board dynamics, Working Paper, Duke University, Cornell University, and Washington University.

Guo, Lixiong, and Ronald W. Masulis, 2015, Board structure and monitoring: New evidence from CEO turnovers, Review of Financial Studies 28, 2770 – 2811.

Harris, Milton, and Bengt Holmström, 1982, A theory of wage dynamics, Review of Economic Studies 49(3), 315-333.

Hazarika, Sonali, Jonathan M. Karpoff, and Rajarishi Nahata, 2012, Internal corporate governance, CEO turnover, and earnings management, Journal of Financial Economics 104(1), 44-69.

He, Zhiguo, 2012, Dynamic compensation contracts with private savings, Review of Financial Studies 25(5), 1494-1549.

Helwege, Jean, Vincent J. Intintoli, and Andrew Zhang, 2012, Voting with their feet or activism? Institutional investors' impact on CEO turnover, Journal of Corporate Finance 18(1), 22-37.

Hermalin, Benjamin, and Michael Weisbach, 1998, Endogenously chosen boards of directors and their monitoring of the CEO, American Economic Review 88, 96-118.

Hermalin, Benjamin, and Michael Weisbach, 2003, Boards of directors as an endogenously determined institution: A survey of the economic literature, Economic Policy Review, Federal Reserve Bank of New York, Issue April, 7-26.

Hermalin, Benjamin, and Michael Weisbach, 2017, Assessing managerial ability: Implications for corporate governance, forthcoming in: Benjamin Hermalin and Michael Weisbach (eds.), Handbook of the Economics of Corporate Governance, Elsevier Science North Holland.

Holmström, Bengt, 1982, Managerial incentive schemes–a dynamic perspective, in: Essays in Economics and Management in Honour of Lars Wahlbeck (Swenska Handelshögkolan).

Huson, Mark R., Robert Parrino, and Laura T. Starks, 2001, Internal monitoring mechanisms and CEO turnover: A long term perspective, Journal of Finance 56, 2265-2297.

Huson, Mark R., Paul H. Malatesta, and Robert Parrino, 2004, Managerial succession and firm performance, Journal of Financial Economics 74, 237-275.

Jensen, Michael C., and Kevin J. Murphy, 1990, Performance pay and top-management incentives, Journal of Political Economy 98(2), 225-264.

Jenter, Dirk, and Fadi Kanaan, 2015, CEO turnover and relative performance evaluation, Journal of Finance 70, 2155-2183.

Jovanovic, Boyan, 1979, Job matching and the theory of turnover, Journal of Political Economy 87(5), 972-990.

Kaplan, Steven N., and Bernadette A. Minton, 2012, How has CEO turnover changed?, International Review of Finance 12(1), 57-87.

Kim, Yungsan, 1996, Long-term firm performance and chief executive turnover: An empirical study of the dynamics, Journal of Law, Economics, and Organizations 12(2), 480-496.

Lel, Ugur, and Darius P. Miller, 2008, International cross-listing, firm performance, and top management turnover: A test of the bonding hypothesis, Journal of Finance 63(4), 1897-1937.

Lie, Erik, 2005, On the timing of CEO stock option awards, Management Science 51(5), 802-812.

Mobbs, Shawn, 2013, CEOs under fire: The effects of competition from inside directors on forced CEO turnover and CEO compensation, Journal of Financial and Quantitative Analysis 48(3), 669–698.

Murphy, Kevin J., 1986, Incentives, learning, and compensation: A theoretical and empirical investigation of managerial labor contracts, RAND Journal of Economics 17(1), 59-76.

Murphy, Kevin J., 1999, Executive compensation, in: Orley Ashenfelter and David Card (eds.), Handbook of Labor Economics Vol. 3b, Elsevier Science North Holland, Chapter 38: 2485-2563.

Parrino, Robert, 1997. CEO turnover and outside succession: A cross-sectional analysis, Journal of Financial Economics 46, 165-197.

Parrino, Robert, Richard W. Sias, and Laura T. Starks, 2003, Voting with their feet: institutional ownership changes around forced CEO turnover, Journal of Financial Economics 68(1), 3-46.

Peters, Florian S. and Alexander F. Wagner, 2014, The executive turnover risk premium, Journal of Finance 69, 1529-1563.

Sannikov, Yuliy, 2008, A continuous-time version of the principal-agent problem, Review of Economic Studies, 75(3), 957-984.

Sattinger, Michael, 1979, Differential rents and the distribution of earnings, Oxford Economics Papers 31, 60–71.

Schwartz-Ziv, Miriam, and Michael Weisbach, 2013, What do boards really do? Evidence from minutes of board meetings, Journal of Financial Economics 108, 349-366

Taylor, Lucian A., 2010, Why are CEOs rarely fired? Evidence from structural estimation, Journal of Finance 65(6), 2051-2087.

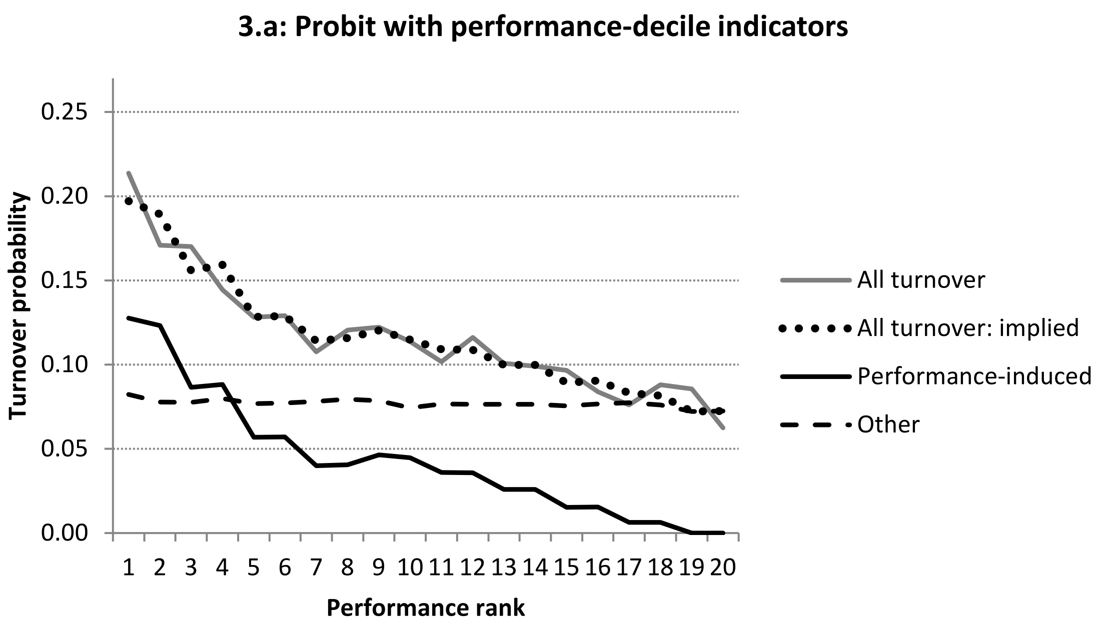
Taylor, Lucian A., 2013, CEO wage dynamics: Estimates from a learning model, Journal of Financial Economics 108, 70-98.

Warner, Jerold B., Ross L. Watts, and Karen H. Wruck, 1988, Stock prices and top management changes, Journal of Financial Economics 20, 461-492.

Weisbach, Michael S., 1988, Outside directors and CEO turnover, Journal of Financial Economics 20, 431-460.

Yermack, David, 2006, Golden handshakes: Separation pay for retired and dismissed CEOs, Journal of Accounting and Economics 41, 237-256.

Fig. 3: Performance-induced and other turnover as a function of performance. The figures depict actual and model-implied CEO turnover probabilities as a function of performance. Implied turnover probabilities are from a probit model with performance decile indicators (3.a) and a two-probit model (3.b). The regression estimates are shown in column (2) of Table 3 and in column (1) of Table 4, respectively. Performance is measured as average monthly stock returns over tenure years [-2,0] scaled by their standard deviation. Implied probabilities are calculated for each observation (leaving performance and control variables at their actual values) and then averaged within 20 performance percentile ranks.



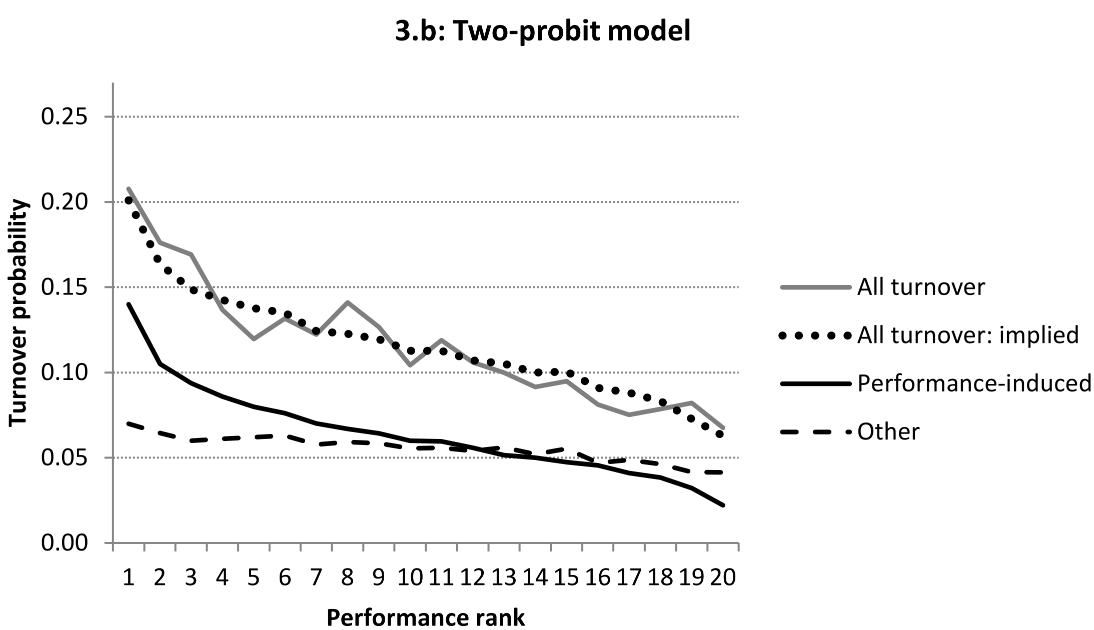
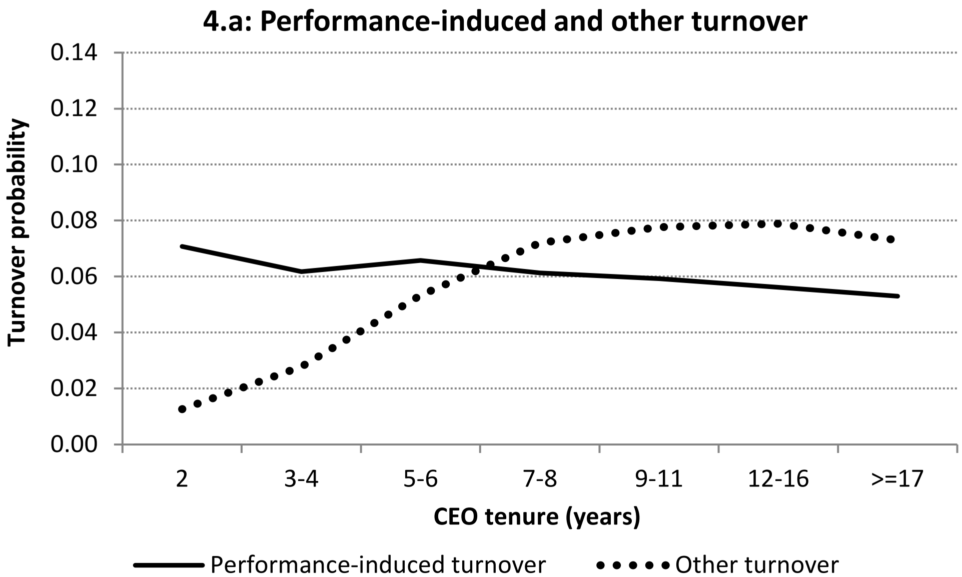


Fig. 4: Turnover probabilities as a function of CEO tenure. The figures show model-implied turnover probabilities as a function of CEO tenure. Implied probabilities of performance-induced and other turnover (4.a) are from the two-probit model in Table 7. Implied probabilities of forced and voluntary turnover (4.b) are from the standard probit model in Table 8. Implied probabilities are calculated for each observation (leaving performance and control variables at their actual values) and then averaged within tenure bins.



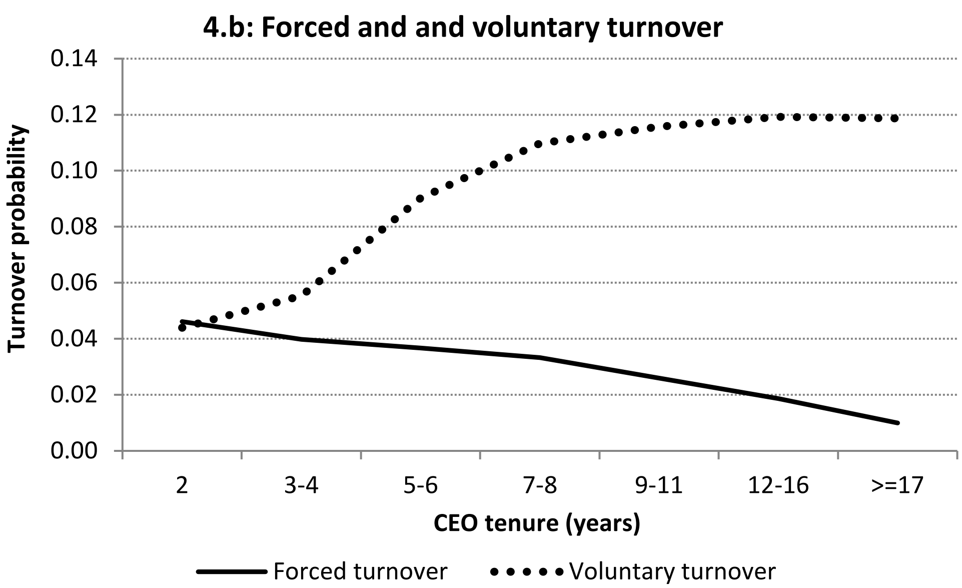


Table 1: Estimating performance-induced turnover: Simulations. The table shows descriptive statistics for estimates from 500 randomly generated samples of 23,000 CEO-years each. In the simulations, performance-induced departures occur with probability $P_{perf-ind} = \Phi(\beta_1 + \beta_2 \cdot x_t)$, other departures occur with probability $P_{other} = \Phi(\alpha_1)$, or both events occur simultaneously. Parameters α_1, β_1, and β_2 are set to -1.4, -1.6, and -0.4, respectively; x_t is normally distributed with mean 0.1 and standard deviation 0.3. Total turnover is governed by eq. (12). The turnover-performance relation $P_{turn}(x_t)$ is estimated using a standard probit model with decile dummies (eq. (10)) or the two-probit model (eq. (11)), with the performance term x_t scaled by its standard deviation. Performance-induced turnover probabilities are calculated using the probit model with decile dummies and eq. (9), with $\hat{X}$ equal to the 90th percentile of performance, or using the $P_{perf-ind}(x_t)$ term in the two-probit model (eq. (11)). In each simulation, implied probabilities are averaged across observations within each performance decile. The bottom panel shows descriptive statistics for the estimated coefficients of the two-probit models across the 500 simulations.

				Performance-induced turnover probabilities (estimated)					
	Dismissals probabilities (observed)			Two-probit			Standard probit with decile dummies		
Perf. decile	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.
1	0.155	0.154	0.008	0.155	0.155	0.009	0.148	0.147	0.009
2	0.094	0.094	0.006	0.095	0.095	0.010	0.087	0.087	0.007
3	0.072	0.072	0.006	0.073	0.072	0.010	0.065	0.065	0.006
4	0.057	0.057	0.005	0.058	0.057	0.010	0.049	0.049	0.006
5	0.046	0.046	0.004	0.047	0.047	0.010	0.039	0.038	0.006
6	0.037	0.037	0.004	0.038	0.037	0.009	0.029	0.029	0.005
7	0.030	0.030	0.003	0.031	0.030	0.009	0.022	0.022	0.004
8	0.023	0.022	0.003	0.024	0.023	0.008	0.015	0.015	0.003
9	0.016	0.016	0.003	0.017	0.016	0.007	0.009	0.009	0.002
10	0.008	0.008	0.002	0.009	0.008	0.005	0.000	0.000	0.000

Two-probit parameter estimates			
Coefficient	Mean	Median	Std.
β_1	-1.598	-1.598	0.090
β_2	-0.401	-0.400	0.050
α_1	-1.408	-1.398	0.058

Table 2: Descriptive statistics. The sample consists of 2,977 ExecuComp firms from 1993 to 2011 with 4,942 CEOs and 23,399 CEO-years. Book assets are in $ millions. Book-to-market is the ratio of the book value to the market value of common equity, where the book value of common equity is defined as shareholders' equity plus deferred taxes plus balance sheet tax credits minus the book value of preferred stock. Dividend payer is an indicator for firms that pay dividends during the fiscal year. ROA is operating cash flow divided by book assets. Book assets, Book-to-market, ROA and Dividend payer are lagged by one year. Book-to-market and ROA are winsorized at the 1% level.

	Mean	Median	P10	P90	Std.
CEO age	56.07	56.00	47.00	65.00	7.50
CEO tenure	10.23	8.00	3.00	21.00	7.79
CEO turnover	0.12	0.00	0.00	1.00	0.32
Book assets	10,190	1,231	152	15,801	57,616
Book-to-market	0.55	0.46	0.17	1.01	0.40
ROA	0.16	0.15	0.03	0.30	0.13
Dividend payer	0.60	1.00	0.00	1.00	0.49

Table 3: Performance-induced turnover using a standard probit model with performance decile indicators. Panel A shows probit regressions of an indicator for CEO turnover on indicator variables for deciles of the performance distribution. Performance is measured as average monthly stock returns scaled by the standard deviation of returns. Returns are measured over tenure years [-1,0], [-2,0], [-3,0], and from tenure start to year 0 in regressions 1, 2, 3, and 4, respectively, where year 0 is the year of the CEO turnover. Panel B shows model-implied turnover probabilities. The probabilities are calculated by setting performance to the desired decile, leaving all control variables at their actual values, and averaging the implied probabilities across all observations. The probability of "other turnover" is calculated by setting performance to the top decile for each observation. The probability of "performance-induced turnover" is calculated for each observation from the difference between the implied total turnover probability and the implied probability of "other" turnover (see equation (9)). *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Panel A: Probit regressions

	(1)		(2)		(3)		(4)	
	Coefficient	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**
	Scaled return t=[-1, 0]		Scaled return t=[-2, 0]		Scaled return t=[-3, 0]		Scaled return t=[tenure start, 0]	
Decile 1	-		-		-		-	
2	-0.185***	[-4.07]	-0.135**	[-2.99]	-0.142**	[-3.21]	-0.121**	[-2.61]
3	-0.223***	[-4.90]	-0.258***	[-5.62]	-0.286***	[-6.21]	-0.177***	[-3.74]
4	-0.349***	[-7.65]	-0.339***	[-7.19]	-0.234***	[-5.21]	-0.235***	[-5.05]
5	-0.289***	[-6.36]	-0.309***	[-6.73]	-0.319***	[-6.83]	-0.248***	[-5.18]
6	-0.349***	[-7.34]	-0.357***	[-7.75]	-0.338***	[-7.20]	-0.376***	[-7.71]
7	-0.339***	[-7.14]	-0.408***	[-8.50]	-0.426***	[-8.93]	-0.357***	[-7.10]
8	-0.429***	[-9.18]	-0.467***	[-9.92]	-0.477***	[-9.89]	-0.413***	[-8.07]
9	-0.551***	[-11.38]	-0.522***	[-10.65]	-0.549***	[-11.00]	-0.345***	[-7.02]
10	-0.523***	[-10.89]	-0.562***	[-11.20]	-0.538***	[-10.58]	-0.441***	[-8.69]
Age	0.0161***	[5.99]	0.0157***	[5.79]	0.0151***	[5.58]	0.0144***	[5.32]
Age 61-63	0.286***	[7.55]	0.289***	[7.59]	0.292***	[7.67]	0.286***	[7.55]
Age 64-66	0.655***	[14.01]	0.659***	[14.04]	0.664***	[14.09]	0.666***	[14.13]
Age > 66	0.365***	[5.70]	0.373***	[5.79]	0.382***	[5.89]	0.372***	[5.76]
Tenure	-0.0100***	[-6.17]	-0.00995***	[-6.13]	-0.00988***	[-6.04]	-0.00599***	[-3.60]
Dividend	-0.0977***	[-3.81]	-0.108***	[-4.18]	-0.115***	[-4.44]	-0.123***	[-4.74]
Log assets	0.0249***	[3.67]	0.0215**	[3.16]	0.0200**	[2.92]	0.0240***	[3.56]
Constant	-1.958***	[-13.49]	-1.895***	[-12.91]	-1.857***	[-12.62]	-1.933***	[-13.07]
N	23,399		23,399		23,399		23,399	

Panel B: Implied turnover probabilities

	(1)	(2)	(3)	(4)
	Scaled return t=[-1, 0]	Scaled return t=[-2, 0]	Scaled return t=[-3, 0]	Scaled return t=[tenure start, 0]
		Total turnover		
Decile 1	18.47%	18.73%	18.58%	17.28%
2	14.11%	15.44%	15.16%	14.48%
3	13.33%	12.81%	12.14%	13.29%
4	10.90%	11.26%	13.19%	12.12%
5	12.01%	11.83%	11.53%	11.88%
6	10.91%	10.93%	11.18%	9.63%
7	11.08%	10.05%	9.65%	9.94%
8	9.54%	9.09%	8.85%	9.03%
9	7.71%	8.26%	7.79%	10.14%
Decile 10	8.11%	7.69%	7.94%	8.60%
All	11.65%	11.65%	11.65%	11.65%
		Performance-induced turnover		
Decile 1	11.50%	12.19%	11.79%	9.70%
2	6.68%	8.57%	8.01%	6.58%
3	5.81%	5.67%	4.67%	5.25%
4	3.11%	3.95%	5.83%	3.95%
5	4.34%	4.58%	3.98%	3.68%
6	3.12%	3.59%	3.60%	1.15%
7	3.31%	2.61%	1.90%	1.50%
8	1.59%	1.55%	1.01%	0.48%
9	0.00%	0.63%	0.00%	1.73%
Decile 10	0.00%	0.00%	0.00%	0.00%
All	3.99%	4.39%	4.14%	3.42%
“Other” turnover	8.11%	7.69%	7.94%	8.60%

Table 4: Performance-induced turnover using the two-probit model. Panel A shows two-probit regressions of an indicator for CEO turnover on firm performance and controls. Performance is measured as average monthly stock returns scaled by the standard deviation of returns. Returns are measured over tenure years [-2,0] in regression 1 and using separate terms for each included tenure year in regressions 2 to 4. Year 0 is the year of the CEO turnover. Panel B shows model-implied turnover probabilities. The probabilities are calculated by setting performance to the desired percentile, leaving all control variables at their actual values, and averaging the implied probabilities across all observations. The probability of "performance-induced turnover" is calculated as the implied probability of the Probit 1 term. The probability of "other turnover" is calculated as the implied probability of the Probit 2 term. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Panel A: Two-probit regressions

	(1)		(2)		(3)		(4)	
	Coefficient	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**
Probit 1:								
Scaled return t=[-2, 0]	-0.298***	[-7.84]						
Scaled return t=0			-0.205***	[-6.69]	-0.194***	[-5.37]	-0.174***	[-4.02]
Scaled return t=-1			-0.226***	[-7.20]	-0.207***	[-5.79]	-0.182***	[-4.38]
Scaled return t=-2			-0.129***	[-5.86]	-0.131***	[-5.02]	-0.130***	[-4.15]
Scaled return t=-3					-0.0604**	[-2.85]	-0.0611**	[-2.61]
Scaled return t=-4							-0.0118	[-0.58]
Age	0.00897	[1.48]	0.00773	[1.33]	0.00929	[1.27]	0.0136	[1.57]
Tenure	-0.00745*	[-2.07]	-0.00784*	[-2.11]	-0.0100*	[-2.16]	-0.0101*	[-1.97]
Dividend	-0.410***	[-6.38]	-0.429***	[-6.80]	-0.419***	[-5.92]	-0.412***	[-4.16]
Log assets	-0.0271	[-1.70]	-0.0302	[-1.83]	-0.0242	[-1.36]	-0.000755	[-0.04]
Constant	-1.548***	[-4.48]	-1.485***	[-4.54]	-1.547***	[-3.76]	-1.889***	[-3.93]
Probit 2:								
Age	0.0382***	[4.59]	0.0372***	[4.72]	0.0344***	[3.93]	0.0311**	[3.11]
Age 61-63	0.441***	[4.29]	0.429***	[4.75]	0.437***	[4.13]	0.487**	[3.16]
Age 64-66	0.898***	[5.70]	0.871***	[6.43]	0.870***	[5.24]	0.939***	[3.75]
Age > 66	0.366*	[2.17]	0.354*	[2.35]	0.359*	[2.11]	0.413	[1.87]
Tenure	-0.0110**	[-2.93]	-0.0104**	[-3.01]	-0.0110**	[-2.77]	-0.0141*	[-2.44]
Dividend	0.446*	[2.46]	0.404*	[2.40]	0.440*	[1.99]	0.550	[1.60]
Log assets	0.0696***	[5.00]	0.0686***	[5.19]	0.0688***	[4.45]	0.0711***	[3.53]
Constant	-4.822***	[-10.39]	-4.686***	[-10.19]	-4.542***	[-9.02]	-4.492***	[-7.19]
N	23,399		23,399		20,100		17,109	

Panel B: Implied turnover probabilities

	(1)	(2)	(3)	(4)
		Total turnover		
5^{th} percentile	18.21%	18.53%	19.04%	19.23%
15^{th} percentile	15.03%	15.08%	15.58%	15.97%
25^{th} percentile	13.48%	13.45%	14.01%	14.50%
35^{th} percentile	12.41%	12.35%	12.93%	13.47%
45^{th} percentile	11.53%	11.46%	12.07%	12.60%
55^{th} percentile	10.79%	10.71%	11.29%	11.81%
65^{th} percentile	10.09%	9.99%	10.59%	11.10%
75^{th} percentile	9.37%	9.26%	9.83%	10.32%
85^{th} percentile	8.61%	8.48%	9.01%	9.45%
95^{th} percentile	7.54%	7.40%	7.86%	8.19%
All	11.66%	11.65%	12.19%	12.68%
		Performance-induced turnover		
5^{th} percentile	13.30%	13.32%	13.65%	14.08%
15^{th} percentile	9.95%	9.69%	9.99%	10.63%
25^{th} percentile	8.32%	7.97%	8.33%	9.06%
35^{th} percentile	7.20%	6.82%	7.18%	7.98%
45^{th} percentile	6.27%	5.87%	6.28%	7.06%
55^{th} percentile	5.50%	5.08%	5.45%	6.22%
65^{th} percentile	4.76%	4.33%	4.71%	5.47%
75^{th} percentile	4.00%	3.56%	3.91%	4.64%
85^{th} percentile	3.21%	2.74%	3.05%	3.73%
95^{th} percentile	2.08%	1.61%	1.83%	2.40%
All	6.43%	6.10%	6.43%	7.17%
"Other" turnover	5.55%	5.87%	6.11%	5.92%

Table 5: Forced turnover regressions. Panel A shows probit regressions of an indicator for forced CEO turnover on firm performance and controls. Performance is measured as average monthly stock returns scaled by the standard deviation of returns. Returns are measured over tenure years [-2,0] in regression 1 and using separate terms for each included tenure year in regressions 2 to 4. Year 0 is the year of the CEO turnover. Panel B shows model-implied turnover probabilities. The probabilities are calculated by setting performance to the desired percentile, leaving all control variables at their actual values, and averaging the implied probabilities across all observations. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Panel A: Forced-turnover probit regressions

	(1)		(2)		(3)		(4)	
	Coefficient	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**
Scaled return t=[-2, 0]	-0.360***	[-17.27]						
Scaled return t=0			-0.222***	[-10.84]	-0.208***	[-9.54]	-0.203***	[-7.97]
Scaled return t=-1			-0.303***	[-14.39]	-0.294***	[-12.70]	-0.300***	[-11.63]
Scaled return t=-2			-0.127***	[-6.34]	-0.133***	[-5.83]	-0.132***	[-5.07]
Scaled return t=-3					-0.0834***	[-3.74]	-0.0893***	[-3.51]
Scaled return t=-4							-0.0576*	[-2.31]
Age	-0.00303	[-0.81]	-0.00322	[-0.85]	-0.00529	[-1.23]	-0.00537	[-1.09]
Age 61-63	-0.453***	[-5.28]	-0.455***	[-5.24]	-0.460***	[-4.94]	-0.451***	[-4.56]
Age 64-66	-0.534***	[-4.00]	-0.531***	[-3.94]	-0.529***	[-3.75]	-0.541***	[-3.58]
Age > 66	-0.375**	[-2.90]	-0.373**	[-2.88]	-0.308*	[-2.31]	-0.287*	[-2.08]
Tenure	-0.0178***	[-4.61]	-0.0176***	[-4.49]	-0.0184***	[-4.12]	-0.0172***	[-3.51]
Dividend	-0.279***	[-6.28]	-0.283***	[-6.35]	-0.266***	[-5.24]	-0.291***	[-5.11]
Log assets	0.0199	[1.54]	0.0224	[1.74]	0.0275	[1.90]	0.0432**	[2.68]
Constant	-1.543***	[-7.85]	-1.573***	[-7.92]	-1.479***	[-6.51]	-1.586***	[-6.07]
N	20,435		20,435		17,552		14,922	

Panel B: Implied turnover probabilities

	(1)	(2)	(3)	(4)
		Forced turnover		
5^{th} percentile	7.25%	7.51%	7.24%	6.73%
15^{th} percentile	4.82%	4.85%	4.63%	4.29%
25^{th} percentile	3.74%	3.69%	3.54%	3.27%
35^{th} percentile	3.03%	2.95%	2.84%	2.60%
45^{th} percentile	2.49%	2.41%	2.33%	2.14%
55^{th} percentile	2.06%	1.97%	1.90%	1.73%
65^{th} percentile	1.68%	1.57%	1.53%	1.37%
75^{th} percentile	1.31%	1.20%	1.17%	1.04%
85^{th} percentile	0.95%	0.81%	0.79%	0.71%
95^{th} percentile	0.51%	0.38%	0.37%	0.33%
All	2.83%	2.83%	2.70%	2.50%

Table 6: Voluntary turnover regressions. Panel A shows probit regressions of an indicator for voluntary CEO turnover on firm performance and controls. Performance is measured as average monthly stock returns scaled by the standard deviation of returns. Returns are measured over tenure years [-2,0] in regression 1 and using separate terms for each included tenure year in regressions 2 to 4. Year 0 is the year of the CEO turnover. Panel B shows model-implied turnover probabilities. The probabilities are calculated by setting performance to the desired percentile, leaving all control variables at their actual values, and averaging the implied probabilities across all observations. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Panel A: Voluntary-turnover probit regressions

	(1)		(2)		(3)		(4)	
	Coefficient	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**
Scaled return t=[-2, 0]	-0.0862***	[-6.55]						
Scaled return t=0			-0.0571***	[-4.34]	-0.0562***	[-4.03]	-0.0581***	[-3.93]
Scaled return t=-1			-0.0550***	[-4.17]	-0.0506***	[-3.64]	-0.0491***	[-3.34]
Scaled return t=-2			-0.0341*	[-2.56]	-0.0388**	[-2.76]	-0.0458**	[-3.05]
Scaled return t=-3					-0.0206	[-1.49]	-0.0209	[-1.39]
Scaled return t=-4							-0.0110	[-0.73]
Age	0.0249***	[7.13]	0.0249***	[7.13]	0.0237***	[6.30]	0.0231***	[5.63]
Age 61-63	0.405***	[9.37]	0.406***	[9.38]	0.396***	[8.73]	0.393***	[8.21]
Age 64-66	0.782***	[14.59]	0.782***	[14.60]	0.759***	[13.48]	0.745***	[12.45]
Age > 66	0.414***	[5.43]	0.414***	[5.43]	0.409***	[5.09]	0.412***	[4.81]
Tenure	-0.00816***	[-4.50]	-0.00810***	[-4.47]	-0.0102***	[-5.37]	-0.0129***	[-6.36]
Dividend	-0.0589*	[-1.98]	-0.0575	[-1.94]	-0.0529	[-1.69]	-0.0443	[-1.31]
Log assets	0.0290***	[3.72]	0.0298***	[3.84]	0.0317***	[3.80]	0.0400***	[4.42]
Constant	-3.008***	[-16.19]	-3.017***	[-16.23]	-2.904***	[-14.48]	-2.871***	[-13.03]
N	20,435		20,435		17,552		14,922	

Panel B: Implied turnover probabilities

	(1)	(2)	(3)	(4)
		Voluntary turnover		
5th percentile	11.89%	11.88%	12.74%	13.67%
15th percentile	10.98%	10.96%	11.74%	12.61%
25th percentile	10.48%	10.47%	11.22%	12.04%
35th percentile	10.10%	10.10%	10.84%	11.62%
45th percentile	9.76%	9.78%	10.50%	11.25%
55th percentile	9.45%	9.47%	10.16%	10.88%
65th percentile	9.13%	9.16%	9.84%	10.51%
75th percentile	8.77%	8.80%	9.45%	10.09%
85th percentile	8.34%	8.35%	8.96%	9.54%
95th percentile	7.59%	7.53%	8.09%	8.62%
All	9.70%	9.70%	10.41%	11.16%

Table 7: Performance-induced turnover across tenure. The table shows a two-probit regression of an indicator for CEO turnover on firm performance and controls. Performance is measured as average monthly stock returns per tenure year scaled by the standard deviation of returns. The performance terms are interacted with indicators for tenure years 3-4, 5-6, 7-8, 9-11, 12-16, and 17 or higher. The interaction coefficients for each tenure period (shown in bold) are reported in the left panel. Year t=0 is the year of the CEO turnover. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Probit 1: Performance-induced turnover		
Tenure year 2		
Scaled return t=0	-0.215***	[-5.30]
Scaled return t=-1	-0.195***	[-4.75]
Tenure years 3-4		
Scaled return t=0	-0.228***	[-5.88]
Scaled return t=-1	-0.268***	[-6.67]
Scaled return t=-2	-0.0753*	[-2.16]
Tenure years 5-6		
Scaled return t=0	-0.192***	[-4.44]
Scaled return t=-1	-0.295***	[-5.37]
Scaled return t=-2	-0.179***	[-4.54]
Tenure years 7-8		
Scaled return t=0	-0.321***	[-5.56]
Scaled return t=-1	-0.249***	[-3.69]
Scaled return t=-2	-0.160*	[-2.54]
Scaled return t=-3	-0.117*	[-2.27]
Tenure years 9-11		
Scaled return t=0	-0.225***	[-3.54]
Scaled return t=-1	-0.176***	[-3.60]
Scaled return t=-2	-0.147**	[-2.82]
Scaled return t=-3	-0.0712	[-1.32]
Tenure years 12-16		
Scaled return t=0	-0.175**	[-2.83]
Scaled return t=-1	-0.137**	[-2.80]
Scaled return t=-2	-0.136**	[-2.62]
Scaled return t=-3	-0.0739	[-1.32]
Tenure years 17+		
Scaled return t=0	-0.119*	[-2.04]
Scaled return t=-1	-0.206***	[-3.65]
Scaled return t=-2	-0.121*	[-2.04]
Scaled return t=-3	-0.106*	[-2.03]

cont.		
Tenure (3,4)	-0.0826	[-1.28]
Tenure (5,6)	-0.0383	[-0.48]
Tenure (7,8)	-0.0997	[-1.08]
Tenure (9-11)	-0.0987	[-1.01]
Tenure (12-16)	-0.139	[-1.44]
Tenure (17+)	-0.210*	[-1.96]
Age	0.00881	[1.74]
Dividend	-0.446***	[-7.33]
Log assets	-0.0498**	[-2.97]
Constant	-1.383***	[-4.67]

Probit 2: Other turnover		
Tenure (3,4)	0.302*	[2.14]
Tenure (5,6)	0.526***	[3.58]
Tenure (7,8)	0.641***	[4.40]
Tenure (9-11)	0.655***	[4.48]
Tenure (12-16)	0.611***	[4.24]
Tenure (17+)	0.276	[1.68]
Age	0.0313***	[3.67]
Age 61-63	0.434***	[5.52]
Age 64-66	0.877***	[7.76]
Age > 66	0.418**	[2.82]
Dividend	0.380*	[2.34]
Log assets	0.0768***	[5.56]
Constant	-4.981***	[-9.42]
N	26,180	

Table 8: Forced turnover across tenure. The table shows a standard probit regressions of an indicator for forced CEO turnover on firm performance and controls. Performance is measured as average monthly stock returns per tenure year scaled by the standard deviation of returns. The performance terms are interacted with indicators for tenure years 3-4, 5-6, 7-8, 9-11, 12-16, and 17 or higher. The interaction coefficients for each tenure period (shown in bold) are reported in the left panel. Year t=0 is the year of the CEO turnover. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Probit: Forced turnover		
Tenure year 2		
Scaled return t=0	-0.219***	[-4.96]
Scaled return t=-1	-0.208***	[-4.59]
Tenure years 3-4		
Scaled return t=0	-0.242***	[-6.17]
Scaled return t=-1	-0.317***	[-8.27]
Scaled return t=-2	-0.113**	[-3.19]
Tenure years 5-6		
Scaled return t=0	-0.175***	[-4.01]
Scaled return t=-1	-0.348***	[-7.39]
Scaled return t=-2	-0.150***	[-3.50]
Tenure years 7-8		
Scaled return t=0	-0.219***	[-4.24]
Scaled return t=-1	-0.349***	[-5.87]
Scaled return t=-2	-0.262***	[-4.30]
Scaled return t=-3	-0.122*	[-2.34]
Tenure years 9-11		
Scaled return t=0	-0.251***	[-4.34]
Scaled return t=-1	-0.199***	[-3.86]
Scaled return t=-2	-0.137*	[-2.32]
Scaled return t=-3	-0.130**	[-2.73]
Tenure years 12-16		
Scaled return t=0	-0.234***	[-3.62]
Scaled return t=-1	-0.326***	[-5.44]
Scaled return t=-2	0.0159	[0.25]
Scaled return t=-3	-0.0993	[-1.57]
Tenure years 17+		
Scaled return t=0	-0.207**	[-2.93]
Scaled return t=-1	-0.242***	[-3.36]
Scaled return t=-2	-0.0948	[-1.29]
Scaled return t=-3	-0.0911	[-1.33]

cont.		
Tenure (3,4)	-0.0888	[-1.53]
Tenure (5,6)	-0.0843	[-1.35]
Tenure (7,8)	-0.120	[-1.69]
Tenure (9-11)	-0.198**	[-2.74]
Tenure (12-16)	-0.373***	[-4.66]
Tenure (17+)	-0.425***	[-4.90]
Age	-0.00608	[-1.71]
Age 61-63	-0.408***	[-4.91]
Age 64-66	-0.486***	[-3.75]
Age > 66	-0.343**	[-2.63]
Dividend	-0.311***	[-7.47]
Log assets	0.0102	[0.82]
Constant	-1.298***	[-6.84]
N	22,887	

Table 9: Performance-induced turnover in different calendar time periods. Panel A shows two-probit regressions of an indicator for CEO turnover on firm performance and controls. Performance is measured as average monthly stock returns per tenure year scaled by the standard deviation of returns. Year 0 is the year of the CEO turnover. Panel B shows model-implied turnover probabilities. The probabilities are calculated by setting performance to the desired percentile, leaving all control variables at their actual values, and averaging the implied probabilities across all observations. The probability of "performance-induced turnover" is calculated as the implied probability of the Probit 1 term. The probability of "other turnover" is calculated as the implied probability of the Probit 2 term. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Panel A: Two-probit regressions

	1993-1999		2000-2005		2006-2011	
	Coefficient	**T-stat.**	**Coefficient**	**T-stat.**	**Coefficient**	**T-stat.**
Probit 1:						
Scaled return t=0	-0.233***	[-4.91]	-0.226***	[-3.66]	-0.123*	[-1.99]
Scaled return t=-1	-0.213***	[-4.89]	-0.234**	[-3.20]	-0.168**	[-2.81]
Scaled return t=-2	-0.157***	[-3.69]	-0.0898*	[-2.14]	-0.170***	[-3.50]
Scaled return t=-3	-0.0809	[-1.85]	-0.0486	[-1.45]	-0.0732	[-1.95]
Age	0.0176*	[2.50]	0.00863	[0.65]	0.00587	[0.37]
Tenure	-0.00826	[-1.48]	-0.0145	[-1.47]	-0.00345	[-0.45]
Dividend	-0.671**	[-3.21]	-0.325**	[-3.11]	-0.298*	[-2.45]
Log assets	-0.0412	[-1.29]	-0.0212	[-0.76]	-0.00858	[-0.25]
Constant	-1.877***	[-4.18]	-1.463*	[-2.07]	-1.585*	[-1.98]
Probit 2:						
Age	0.0305*	[2.35]	0.0281	[1.30]	0.0410*	[2.33]
Age 61-63	0.427***	[3.40]	0.489*	[2.02]	0.43	[1.79]
Age 64-66	1.094***	[6.52]	0.837*	[2.39]	0.786*	[2.05]
Age > 66	0.425	[1.70]	0.418	[1.12]	0.319	[0.81]
Tenure	-0.0199***	[-3.96]	-0.00288	[-0.43]	-0.015	[-1.53]
Dividend	0.894	[1.84]	0.494	[1.20]	0.159	[0.75]
Log assets	0.0685*	[2.49]	0.0583	[1.94]	0.0790*	[1.96]
Constant	-4.604***	[-5.25]	-4.243**	[-3.26]	-4.825***	[-5.54]
N	6,358		6,759		6,936	

Panel B: Implied turnover probabilities

	1993-1999	2000-2005	2006-2011
		Total turnover	
5^{th} percentile	18.52%	21.18%	17.72%
15^{th} percentile	15.19%	17.03%	14.71%
25^{th} percentile	13.57%	15.25%	13.28%
35^{th} percentile	12.43%	13.99%	12.34%
45^{th} percentile	11.52%	13.01%	11.58%
55^{th} percentile	10.77%	12.09%	10.89%
65^{th} percentile	10.08%	11.32%	10.27%
75^{th} percentile	9.35%	10.48%	9.58%
85^{th} percentile	8.66%	9.43%	8.82%
95^{th} percentile	7.83%	8.05%	7.67%
All	11.64%	13.19%	11.72%
		Performance-induced turnover	
5^{th} percentile	12.38%	16.20%	12.89%
15^{th} percentile	8.85%	11.82%	9.71%
25^{th} percentile	7.14%	9.95%	8.20%
35^{th} percentile	5.94%	8.62%	7.21%
45^{th} percentile	4.97%	7.58%	6.41%
55^{th} percentile	4.18%	6.62%	5.68%
65^{th} percentile	3.46%	5.81%	5.02%
75^{th} percentile	2.69%	4.92%	4.29%
85^{th} percentile	1.96%	3.82%	3.50%
95^{th} percentile	1.10%	2.36%	2.28%
All	5.14%	7.80%	6.57%
		"Other" turnover	
All	6.78%	5.80%	5.51%