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. Compared to 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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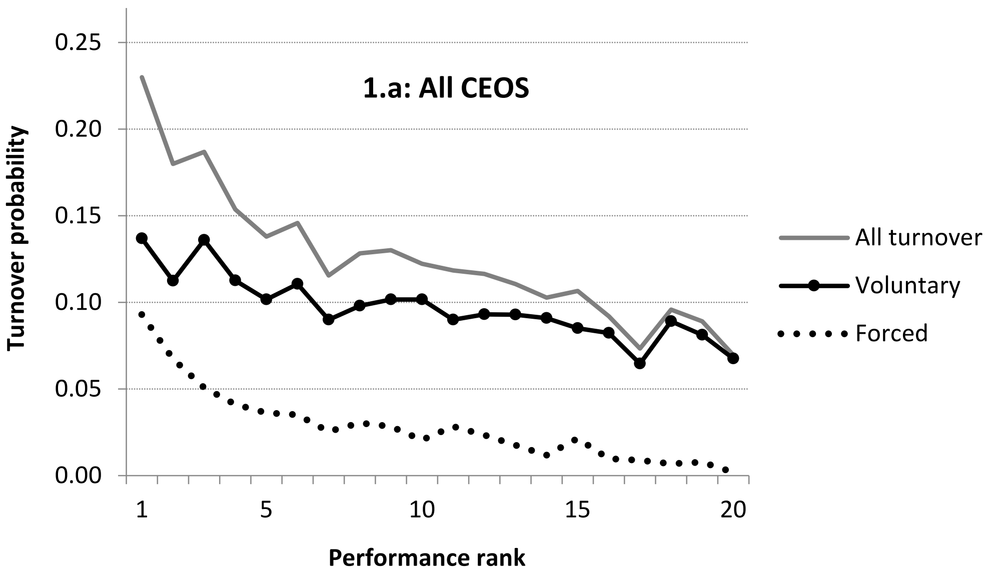
Replacing badly performing CEOs is one of the key responsibilities of corporate boards, and the relationship between CEO turnover and firm performance has been studied extensively. The prior literature has found only modest effects of firm performance on forced turnover. Depending on the sample and the 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 typically 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), Denis and Denis (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.



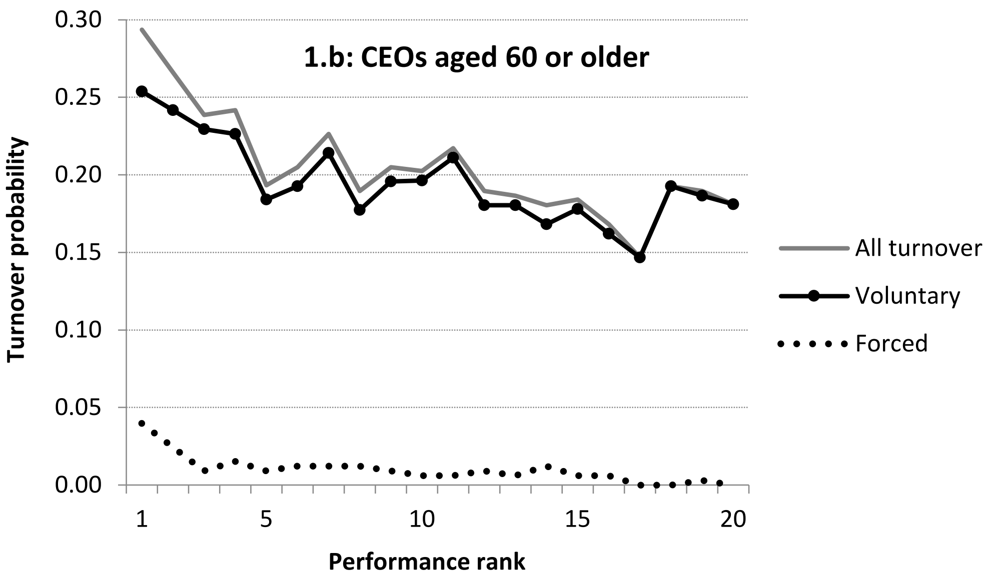


Fig. 1: Probability of forced and voluntary turnover as a function of performance. The figure shows average turnover rates within 20 performance percentile ranks. Performance is measured as the average industry-adjusted stock return in years -2 to 0 before the turnover year. Forced turnovers are identified 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 their increase to performance-induced turnover.

We present two applications of our framework. First, 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] For this application, and consistent with those models, we assume that all (performance-induced) turnovers are due to boards dismissing badly performing CEOs.

The evidence rejects the literature's workhorse model, in which boards learn from firm performance about constant CEO ability. Because of constant ability, the model predicts that boards assign the same weight to all past performance signals. Empirically, however, 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 signals shows little to no decline for at least the first ten years of CEO tenure. This lack of a decline suggests that boards are unable to figure out CEO ability even after observing performance for many years.

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[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 potentially consistent with a version of the Bayesian learning model in which CEO ability is subject to large unobservable shocks (Kim 1996; Garrett and Pavan 2012).[5] If CEO ability changes, boards optimally assign larger weight to more recent performance, which is most informative about current ability. With changing ability, boards' beliefs also remain sensitive to new performance signals even late in tenure. Alternatively, mechanisms further from the literature's standard model might explain the data – a possibility we explore in Section 4.5.

As our second application, we examine CEO turnovers around corporate events that, based on the prior literature, are associated with large increases in turnover. We focus on four kinds of corporate misconduct, on activist campaigns, and on institutional exits. Such adverse events are correlated with firm performance, might directly affect the board's estimate of CEO ability, and likely put pressure on boards to take action. Our analysis reveals large increases in performance-induced (but not other) turnover around all three types of events. Including the events in our empirical model of CEO turnover improves its explanatory power. The events appear to lower boards' assessment of CEO quality or, equivalently, to strengthen boards' resolve, with the result that smaller performance declines are required to trigger turnovers.

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

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

[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.

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.

Performance-induced turnover is, therefore, a distinct concept from forced turnover that is of interest in its own right. Some CEO departures are performance induced without being forced (e.g., CEOs choosing to retire because of bad performance), while others are forced without being performance induced (e.g., CEOs fired because of personal scandals). Whether a research project should use performance-induced or forced turnover depends on the question asked. Conceptually, performance-induced turnover is the right choice if the focus is on whether bad performance causes CEO-firm matches to end; forced turnover is the right choice when the focus is on firing decisions by boards. In practice, however, given how difficult it is to identify forced turnovers, both performance-induced turnover and algorithmically-classified forced turnover might serve as imperfect proxies for true forced turnover.[6]

We proceed as follows. Section 1 describes the estimation of performance-induced turnover. Section 2 describes the data and provides summary statistics. Section 3 presents the baseline estimates of performance-induced turnover and compares performance-induced to forced turnover. Sections 4 and 5 present two applications, and the final section concludes.

1 Performance-induced turnover

Estimating models of CEO dismissals requires distinguishing firings from other CEO departures. 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.[7] To address this problem, the prior literature

[6] For example, in Section 4 we use both performance-induced and forced turnover (identified using the Parrino algorithm) to test models in which all turnovers are performance-induced firings. Yet, our measure of performance-induced turnover includes CEOs choosing to leave because of bad performance, while Parrino's definition of forced turnover includes almost any abrupt departure by CEOs below age 60.

[7] 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.

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; Denis and Denis 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 anything between these two extremes is of secondary importance.[8] 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 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 and goes to zero as performance goes to infinity:

$$P_{turn}\left(x_t\right) = P_{other} + P_{perf.-ind.}\left(x_t\right) - P_{other} \cdot P_{perf.-ind.}\left(x_t\right) \tag{1}$$

The last term is an adjustment for CEOs that experience both performance-induced turnover and other, not performance-related turnover in the same year.[9]

We are interested in estimating the process for performance-induced turnover. Reordering equation (1) yields

$$P_{perf.-ind.}\left(x_t\right) = \frac{P_{turn}\left(x_t\right) - P_{other}}{1 - P_{other}} \tag{2}$$

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[8] 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.

[9] 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.

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 (2) 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 1.1 and 1.2, 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.

1.1 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.[10] 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 $\hat{X}$:[11]

$$P_{perf-ind}\left(x_t, \hat{X}\right) = \frac{Max\left(P_{turn}\left(x_t\right) - P_{turn}\left(x \geq \hat{X}\right),\, 0\right)}{1 - P_{turn}\left(x \geq \hat{X}\right)} \tag{3}$$

To estimate $P_{perf-ind}(x_t, \hat{X})$ from eq. (3), 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

[10] A violation of this assumption would lead us to underestimate the frequency of performance-induced turnover. See Section 1.4 for further discussion.

[11] 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 types of turnover in the same year.

performance and, thus, delivers a reliable estimate of $P_{other} = P_{turn}(x \geq \hat{X})$. A standard probit or logit model with linear performance terms, as used in much of the prior literature, 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 or logit 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:[12]

$$P_{turn}(x_t) = \Phi(\beta_1 + \beta_2 \cdot Dec_2 + \cdots + \beta_{10} \cdot Dec_{10} + \gamma' \cdot Z_t) \tag{4}$$

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 is calculated as the implied turnover probability with performance in the top decile: $P_{other} = P_{turn}(x \geq \hat{X}_{90th\_percentile})$. Given this estimate, the probability of performance-induced turnover is calculated from equation (3).

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. (4) do not correspond to the coefficients of the Bayesian learning models in Section 4 and, hence, cannot be used to test these models.

1.2 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:

$$\begin{aligned} P_{turn}(X_t) &= P_{other} + P_{perf-ind}(x_t) - P_{other} \cdot P_{perf-ind}(x_t) \\ &= P_{other} + (1 - P_{other}) \cdot P_{perf-ind}(x_t) \end{aligned} \tag{5}$$

[12] We use probit rather than logit models because of the probit's close connection to the Bayesian learning models analyzed in Section 4.

$$= \Phi_{other}(\alpha_1 + \alpha_2 \cdot Z_{1t}) + \big(1 - \Phi_{other}(\alpha_1 + \alpha_2 \cdot Z_{1t})\big)\Phi_{perf-ind}(\beta_1 + \beta_2 \cdot X_t + \gamma' \cdot Z_{2t})$$

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 4, and, hence, can be used to test 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.

1.3 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:

$$P_{turn}(x_t) = P_{other} + P_{perf-ind}(x_t) - P_{other} \cdot P_{perf-ind}(x_t) \qquad (6)$$

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 3. 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.

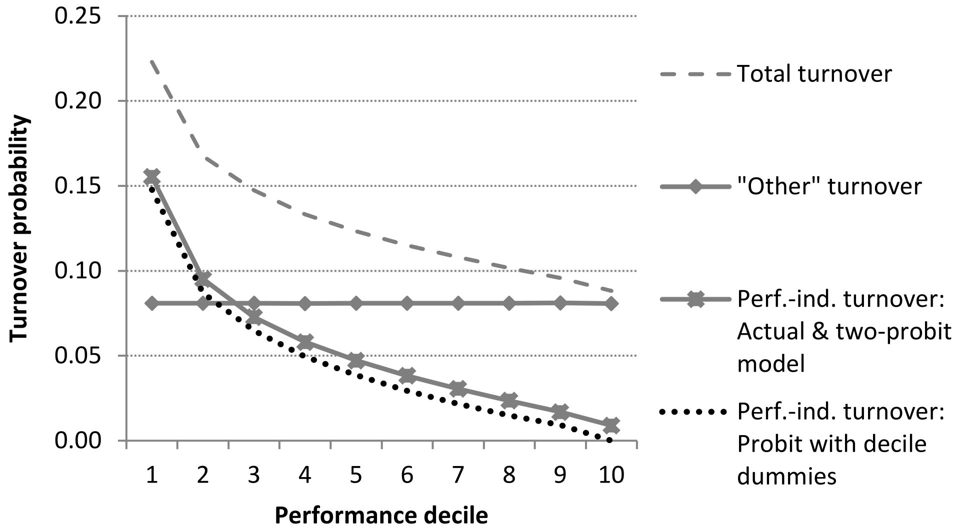

Fig. 2: Estimating performance-induced turnover: numerical example. The simulated sample has 1,000,000 CEO-years. Performance-induced departures occur with probability $P_{perf-ind} = \Phi(\beta_1 + \beta_2 \cdot x_t)$ and other departures occur with probability $P_{other} = \Phi(\alpha_1)$. Parameters 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. (6). The turnover-performance relation $P_{turn}(x_t)$ is estimated using a standard probit model with decile dummies (eq. (4)) or the two-probit model (eq. (5)), 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. (3), 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. (5)). All probabilities shown are averages within 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 estimation 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 recover structural parameters of the underlying model from the data. We will make use of this in Section 4 to estimate Bayesian learning models of CEO turnover.

1.4 Discussion

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 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 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 it does not require the researcher to 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.

Whether a research project should use performance-induced or forced turnover depends on its goals. Performance-induced turnover is the natural choice if the question is whether poor performance causes CEO-firm matches to end, independently of the specific mechanism. Forced turnover is the natural choice if the focus is on firing decisions by boards. This includes, for example, questions of how active boards are in removing poorly performing CEOs, or what type of information they use to assess CEOs.

In practice, however, identifying forced turnovers is difficult, as it is usually in the interest of both the board and the CEO for departures to look voluntary. As a result, measuring forced departures using observed attributes of turnovers, such as explicit firings or sudden departures, is likely to underestimate how active boards are. To address this concern, performance-induced turnover can be used as an alternative proxy for forced turnover – one that encompasses a broader set of turnovers.[13] We illustrate this approach in Section 4, where we use both performance-induced and forced turnover (classified using the Parrino algorithm) as imperfect proxies for performance-induced firings by boards.

There are also several caveats related to the estimation of performance-induced turnover. 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.

Using a standard probit model with performance-decile indicators to estimate performance-induced turnover 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., turnovers that would not have happened had performance been lower). An example are successful CEOs who are hired away by other firms.[14] Both

[13] Performance-induced turnover might overestimate or underestimate board activity as it includes voluntary departures caused by poor performance, but it excludes firings for non-performance reasons.

[14] Cziraki and Jenter (2019) 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.

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 can be reduced by increasing $\hat{X}$, which should lower the number of turnovers above $\hat{X}$ that are 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 3. In smaller samples, however, the estimates can become unstable and highly sensitive to the relatively small number of turnovers at high levels of performance. Because both estimation methods have advantages and disadvantages, we show estimates from both methods below.

2 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 6,385 CEO spells in 3,153 firms, with 31,652 CEO-years and 3,521 turnovers. Merging with control variables and requiring that each CEO has at least three years of performance data reduces the sample to 4,963 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 3.3 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 yields 879 forced and 2,395 voluntary turnovers in 27,708 CEO-years. Merging with control variables and requiring three years of performance data reduces the sample to 619 forced and 1,941 voluntary turnovers in 20,435 CEO-years.[15]

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 industry-adjusted 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.[16]

3 Performance-induced turnover: baseline estimates

This section presents empirical estimates of performance-induced turnover using the two estimation approaches described earlier: the standard probit with performance decile indicators and the two-probit model. Section 3.1 describes the baseline results, Section 3.2 interprets the magnitudes, and Section 3.3 compares performance-induced to forced turnover.

3.1 Baseline estimates

Estimates of performance-induced turnover from standard probit models with performance-decile indicators are in Table 3. The dependent variable is set to one for tenure years with any type of CEO turnover and to zero otherwise. The key independent variables are decile indicators for the firm's stock price performance. Performance is measured as average

[15] There are fewer classified turnovers than in the full sample because the Parrino sample is one year shorter and because missing information prevents us from classifying some turnovers.
[16] All results are qualitatively unchanged without this normalization.

industry-adjusted 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.[17]

The coefficient estimates in Panel A confirm that CEO turnover increases as firm performance decreases. The model-implied turnover probabilities are reported in Panel B. Using equation (3), 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 Section 1.1, 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 $\hat{X}$.

Panel B reveals 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%.[18] Measuring performance over three years yields the steepest turnover-performance slope and a performance-induced turnover probability of 4.4% per year (model (2)). Compared to a total turnover rate of 11.7%, this suggests that 38% of all turnovers are performance induced.

Performance-induced turnover can alternatively be estimated using the two-probit model. 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

[17] Including ROA and market-to-book leaves the results unchanged or strengthens them. Because these controls capture aspects of firm performance, they complicate the interpretation of the results.
[18] We examine the effects of performance at different lags more carefully in Section 4.2.

indicators for retirement age (61-63, 64-66, and 66+). The other 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. Interestingly, larger and dividend-paying firms experience more "other" but less performance-induced turnover.[19] Panel B reports the model-implied turnover probabilities. The two-probit model yields higher estimates of performance-induced turnover than the standard probit. Measuring performance over three years (model (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 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.

3.2 Interpreting the magnitudes

Figure 3 depicts actual and model-implied CEO turnover rates as a function of performance using estimates from the probit with decile indicators (Figure 3.a) and from the two-probit model (Figure 3.b). Both models match the empirical turnover-performance relationship closely, but they diverge on how the overall turnover rate is split between performance-induced and "other" turnover. As explained in Section 1.4, because of the ad-hoc assumption that there are no performance-induced turnovers above the 90th percentile of the performance distribution, the probit with decile indicators delivers a downward-biased estimate 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.[20]

Despite their differences, both estimation approaches show that performance has a larger effect on CEO turnover than suggested by the prior literature. There are, nevertheless, at least

[19] There are several potential explanations for these patterns. For example, CEOs of larger and more mature firms might be more entrenched, or their stock returns might be less informative about CEO performance.
[20] 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. 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.

two reasons to believe that our estimates of performance-induced turnover understate the true frequency. Firstly, the actual performance measure(s) used by boards to evaluate CEOs are unknown, introducing measurement error into the estimation. The performance of a CEO has many dimensions, and boards have access to performance signals that are unobservable to the econometrician.[21] Using an imperfect performance measure implies that we underestimate the effect of (correctly measured) performance on CEO turnover.

Secondly, 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 returns for CEO turnover and biases the estimates of performance-induced turnover downward.[22]

3.3 Comparing performance-induced and forced turnover

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.[23] Hence, our estimates in Section 3.1 suggest that there are substantially more performance-induced than forced turnovers. This is all the more surprising given that forced turnovers include, e.g., CEO dismissals for personal scandals unrelated to firm performance.

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, introduced by Parrino (1997), uses press reports, the time between the turnover announcement and the actual turnover, and the CEO's age at

[21] Cornelli, Kominek, and Ljungqvist (2013) provide evidence for the importance of "soft" information in the evaluation and firing of CEOs.
[22] 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).
[23] Using different algorithms, the percentage of CEO turnovers classified as forced is 20% in Warner, Watts, and Wruck (1988), 18% in Denis and Denis (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% 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).

departure to classify turnovers as either forced or voluntary.[24] 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 619 forced and 1,941 voluntary turnovers in 20,435 tenure years.

A direct comparison between forced and performance-induced turnovers is complicated by the fact that, even though the two-probit model estimates the likelihood of performance-induced turnover, it does not classify any turnovers. To overcome this, we use implied probabilities from the two-probit model to categorize any turnover with a greater than 50% probability of being performance induced as "performance induced," and all other turnovers as "not performance induced."[25] Panel A of Table 5 shows all CEO turnovers in our sample sorted into four groups based on whether they are forced or performance induced. Panel B shows firm and CEO characteristics of turnovers for which the two classifications "agree" (the left-most and right-most panels) or "disagree" (the two middle panels).

The two classifications are highly correlated. For example, Panel A shows that 82% of forced turnovers are also classified as performance induced. However, the overlap is far from perfect. Most notably, 41% of supposedly voluntary turnovers are categorized as performance induced. Panel B (column 5) shows that these "voluntary" departures are associated with poor prior performance (average 3-year CAR of -12%) and occur in firms with a relatively low incidence of "other" turnover (i.e., small and non-dividend paying firms). As a result, the two-probit model estimates a high probability that these turnovers are in fact performance induced.

Of particular interest in the CEO turnover literature has been the link between forced turnover and firm performance. Researchers typically regress an indicator for tenure years with a forced turnover on measures of firm performance. Table 6 presents such standard forced turnover probit regressions using the same performance measures and control variables as in the previous section. Consistent with prior studies, forced turnover is strongly related to firm performance (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

[24] 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).

[25] The implied probabilities are calculated from model (2) in Table 4.

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 assume that boards consider three years of performance (model (1)), the probability of forced turnover rises to 7.3% at the 5th performance percentile, much below the rate of 12.2-13.3% for performance-induced turnover in Tables 3 and 4.

The reason why there are more performance-induced than forced turnovers is simple: Turnovers classified as "voluntary" by the Parrino algorithm are much more frequent at lower levels of performance, suggesting that many of them are in fact performance induced. To show this more rigorously, Table 7 presents regressions of an indicator for voluntary turnover on firm performance and the same control variables as in Table 6. 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).[26] Because the prior literature focuses on forced turnovers and ignores this increase, it underestimates the number of turnovers caused by bad performance.

4 Application: Evaluating Bayesian learning models of CEO turnover

In the remainder of the paper, we present two applications of our framework. In Section 4, we test the predictions of a standard Bayesian learning model of CEO turnover. In Section 5, we examine performance-induced turnover around corporate scandals, activist campaigns, and institutional shareholder exits.

4.1 A simple Bayesian learning model of CEO turnover

This section describes a simple Bayesian learning model of CEO turnover, with all technical details relegated to Appendix A. Its ingredients are based on the more complex models in Jovanovic (1979), Harris and Holmström (1982), Murphy (1986), Gibbons and Murphy (1992), Hermalin and Weisbach (1998), and Taylor (2010).

[26] 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.

4.1.1 Constant CEO ability

A corporate board hires a new CEO of constant but uncertain and unobservable ability. The board updates its beliefs about CEO ability each year after observing a signal of ability, such as the firm's performance. The updating follows Bayes' rule. As is standard in the literature, we assume that firm performance each year equals the CEO's true unobserved ability plus a normally distributed i.i.d. noise term with zero mean. The board fires the CEO once the mean of its posterior estimate of CEO ability falls below an endogenous threshold.[27] This simple framework has two testable implications, derived in Section A.1 of Appendix A:

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

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.

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. 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, which makes this speed empirically observable.

4.1.2 Changing CEO ability

The models in the prior literature almost always assume that CEO ability is constant.[28] 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 Appendix Section A.2, we therefore extend our learning model by assuming that the CEO's true ability follows a random walk with unobservable shocks to ability. Performance each year reflects the CEO's current ability. The model with changing ability has two testable implications:

[27] This threshold results from 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.

[28] 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.

3. When forming beliefs about changing 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.

4. 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. If the sensitivity does not decline with tenure, then boards' beliefs about CEO ability are not converging.

4.1.3 Estimation

To estimate Bayesian learning models of CEO turnover, one needs to add a mean-zero noise term to the relationship between firm performance and the board's estimate of CEO ability. If the noise term is normally distributed, the model can be estimated as a probit regression of an indicator for CEO turnover on current and lagged performance. As shown in Appendix Section A.3, the latent variable in this probit model is the board's estimate of CEO ability, and the probit coefficients estimate the weights the board assigns to prior firm performance when assessing ability. This allows us to test model predictions (1) through (4).

4.2 How much performance history do boards use?

The Bayesian learning model with constant CEO ability predicts that boards assign the same weight to all lags of the performance signal (*Prediction 1*). To test this prediction, we include separate performance terms for the current tenure year, the previous tenure year, etc., in the CEO turnover regressions in Tables 4 and 6. Both the two-probit model for performance-induced turnover (Table 4) and standard forced turnover regressions (Table 6) accommodate multiple lags of performance. If boards assign the same weight to current and past performance, we should find similar coefficients on all the performance terms. This test of the model implicitly assumes that board decisions to remove underperforming CEOs are the only cause of (performance-induced and forced) turnovers.

The Bayesian learning model with constant CEO ability is strongly rejected by the data. In the two-probit model (Table 4), boards assign significantly higher weight to recent performance in tenure years 0 and -1 than to prior years. In specification (3), which includes four years of performance, the coefficient on performance declines monotonically from -0.21 for tenure year -1 to -0.06 for tenure year -3. 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.[29] Including an additional performance term for tenure year -4 in model (4) yields an insignificant coefficient of -0.01.

Forced turnovers are also much more closely linked to recent performance than to performance in the more distant past (Table 6). In model (3) of Table 6, which again includes four years of performance, the coefficient on performance declines monotonically from -0.29 for tenure year -1 to -0.08 for tenure year -3. Using Wald tests, the chi-squared statistics for the 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 6 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 4.1.2). 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 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, 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 6 also suggest that turnover regressions that use only one performance term are misspecified. These regressions implicitly impose the same weight on

[29] 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.

performance at all lags within the performance window, while in reality boards put more 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.

4.3 Performance-induced turnover across tenure

We next explore how performance-induced turnover changes with CEO tenure. The Bayesian learning model with constant CEO ability predicts that the performance sensitivity of boards' beliefs about CEO ability declines with tenure (*Prediction 2*). As boards' beliefs become more precise, each performance signal affects these beliefs less. Consequently, the coefficients on performance in turnover regressions should shrink as tenure increases. To test this prediction, we estimate a two-probit model, similar to that in Table 4, specification (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 8.

There are three important results. Firstly, 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 as 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.

Secondly, 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 4.2. For example, in tenure years 7-8, the coefficient on prior performance declines from -0.25 for year -1 to -0.12 for year -3. Even in tenure years 12-16, only current performance and performance in the previous two years have 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.

Thirdly, 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%, and 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 8 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 weight to more recent performance signals than to older ones (*Prediction 3*). With changing 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 (*Prediction 4*).

The shocks to CEO ability that reconcile the Bayesian learning model with the data would again 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 ability have to offset the boards' learning. The large sensitivity of turnover to current performance shows that performance is informative about CEO ability, yet shocks to ability are apparently large enough to reverse any gains in the precision of boards' beliefs.

4.4 Forced turnover across tenure

The prior section's conclusions are not an artifact of focusing on performance-induced turnover: Repeating the analysis with forced turnovers in Table 9 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 algorithms classifying forced turnovers: Tenure and age are highly correlated, and almost all algorithms assume that turnovers at or above typical retirement ages are 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.

4.5 Discussion: other determinants of CEO turnover

The evidence in this section rejects the model with constant CEO ability (Section 4.1.1) but is potentially consistent with a model with rapidly changing CEO ability (Section 4.1.2). However, several caveats apply to this interpretation. Firstly, 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 in these models. For example, CEOs who give up because of bad performance play no role in the models but are included in performance-induced turnover. It is, therefore, possible that our tests misattribute some CEOs' personal decisions to leave to pressure by boards. Replicating the tests using forced turnover mitigates this concern.

Secondly, the highly-stylized learning models of Section 4.1 at best capture some of the determinants of CEO turnover, and the patterns we observe might be driven by factors outside those models. However, our evidence does not necessarily point to any of the other popular models in the CEO turnover literature. For example, models of learning-by-doing (Garen 1988) or of endogenous entrenchment that increases with tenure (Hermalin and Weisbach 1998, 2003) make the central prediction that performance-induced turnover should decline with tenure. Our finding that performance-induced turnover is almost constant in tenure years two to eight and then declines slowly (Figure 4) does not by itself reject these models. It does, however, suggest that other factors, such as slow learning about CEO ability or high turnover costs, dominate.

Dynamic moral hazard models that include CEO dismissals in their optimal contracts might offer an alternative explanation for our results.[30] In these models, 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 match the observed performance-induced turnover rate, its dependence on recent performance, and its evolution with tenure is an interesting and open question.

Finally, boards might learn about CEO ability from private signals, for example through personal interactions in board meetings. Learning from private signals creates an omitted variable bias when regressing CEO turnover on lagged firm performance (the public signal).[31] This bias might be more severe for older public signals, which could explain why older signals appear to affect turnover less. However, private signals cannot explain why boards' beliefs remain sensitive to new public signals even late in tenure. If anything, learning from private signals should allow boards' beliefs to converge faster.

5 Application: CEO turnover around adverse corporate events

The prior literature shows that CEO turnover increases sharply around certain disruptive events, such as corporate misconduct and activist campaigns. Such events might put pressure on boards to take action against CEOs, might affect boards' assessment of CEO quality, or might reduce CEOs' utility from staying in office. To better understand what explains the increased turnover rates, we examine both performance-induced and forced turnover around such events and incorporate the events directly into our empirical model of CEO turnover. Our analysis focuses on three types of events: corporate misconduct, activist campaigns, and institutional exists.

[30] 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).

[31] Take an incumbent CEO who had bad firm performance in t=-1. The fact that the CEO is still in office at the start of t=0 makes it likely that the board's private signal in t=-1 was positive. This creates a negative correlation between past public and private signals for surviving CEOs, which biases the coefficients on the public signals downwards.

5.1 *Corporate misconduct*

We start by analyzing four types of misconduct in which the firm or the CEO are implicated. The events fall into four categories, discussed in more detail in Appendix C.1: (1) enforcement actions for financial misrepresentation by the Security and Exchange Commission or the Department of Justice; (2) accounting restatements due to accounting irregularities; (3) securities class action lawsuits filed under the Federal Exchange Acts of 1933/1934; and (4) option backdating scandals.[32] Our panel includes 412 CEOs who are in office at the end of a period of (subsequently revealed) corporate misconduct.[33]

Table 10 Panel A shows the frequency with which affected CEOs leave office during the five tenure years starting with the year in which the misconduct ends.[34] CEO turnover is significantly elevated during this period, with an average departure rate of 21% per year, compared to only 12% in other years. There is considerable heterogeneity, with class action lawsuits associated with a turnover rate of 26% per year, yet backdating scandals with a turnover rate of only 16%.

Panel B examines the 231 post-misconduct turnovers. The Parrino algorithm classifies 49% of these turnovers as forced, many more than the 22% in other years. This increase is consistent with the prior literature and arguably unsurprising, as many of these departures are likely to be genuinely and observably forced.[35] Post-misconduct turnovers are also unusually likely to be performance induced. Shown in the third column of Panel B, the two-probit model estimates a 63% probability that post-misconduct turnovers are performance induced, compared to only 51% in other years. One important reason is that post-misconduct turnovers are preceded by

[32] The four misconduct datasets come from multiple sources, including Call, Martin, Sharp, and Wilde (2018), Beneish, Marshall, and Yang (2016), Dyck, Morse, and Zingales (2010), and the June 2007 Glass-Lewis & Co. Yellow Card Trend Alert Report (Carow, Heron, Lie, and Neal 2009; Ertimur, Ferri, and Maber 2012). See Appendix C.1 for more information.

[33] The total number of misconduct events is larger as some CEOs are associated with more than one event (especially restatements and SEC/DOJ enforcement actions).

[34] Karpoff, Lee, and Martin (2008) and Karpoff, Koester, Lee and Martin (2017) describe the protracted process of regulatory enforcement for financial misrepresentation, which for typical cases stretches over almost five years.

[35] Karpoff, Lee, and Martin (2008) show that the vast majority of managers identified as culpable in SEC or DOJ enforcement actions lose their jobs. Several studies document increased CEO turnover following earnings manipulation and accounting restatements, especially if the misstatements are intentional rather than errors (e.g., Arthaud-Day, Certo, Dalton, and Dalton, 2006; Desai, Hogan, and Wilkins, 2006; Hennes, Leone, and Miller, 2008; Burks, 2010; Hazarika, Karpoff, and Nahata, 2013). Strahan (1998) and Niehaus and Roth (1999) observe increased CEO turnover after the filing of a securities class action lawsuit. Efendi, Files, Ouyang, and Swanson (2013) document a large increase in forced CEO turnover after the revelation of option backdating. This literature is surveyed by Karpoff, Koester, Lee and Martin (2017).

poor firm performance, with an average 3-year pre-turnover CAR of -28%, compared to -5% for other turnovers.

To further examine this increase in performance-induced turnover, we incorporate the misconduct events directly into our empirical model of CEO turnover. Using the Bayesian learning model from Section 4 as a guide, misconduct might affect turnover through several channels. Firstly, boards might treat misconduct as a distinct negative signal about CEO ability, which would increase CEO turnover if the CEO is sufficiently close to the firing threshold. Secondly, misconduct might change the board's firing threshold if, for example, pressure from regulators or shareholders changes the cost of a firing. Thirdly, boards might attribute poor post-misconduct performance more strongly to the CEO than performance in other situations, strengthening the link between performance and perceived CEO ability. Finally, misconduct might make retaining the CEO untenable at all levels of performance. This might occur if, for example, the CEO committed a crime and the board is forced to remove him.[36]

To explore these channels, we include an indicator for misconduct in both terms ($P_{perf-ind}$ and P_{other}) of the two-probit model and interact the indicator with performance in the $P_{perf-ind}$ term. The misconduct indicator identifies the period starting with the tenure year in which the misconduct concludes and ending one year to four years later (models (1)-(4)). The results, presented in Table 11, show a significant positive coefficient on the misconduct indicator in the $P_{perf-ind}$ term.[37] This suggests that boards treat misconduct (or information associated with it) as a distinct negative signal of ability or, equivalently, that boards increase the firing threshold for implicated CEOs. The effect is large: based on model (1), misconduct increases the implied probability of performance-induced turnover by 10.25 percentage points, from 6.22% to 16.46% per year (holding all other variables at their actual values).

The coefficient on the interaction of misconduct with performance in the $P_{perf-ind}$ term is insignificant. Within the Bayesian learning model, this indicates that boards do not attribute poor performance more strongly to CEOs after misconduct than in other years. There is also no significant effect of misconduct on other, not performance-induced turnover (P_{other}), which

[36] Misconduct can also affect CEO turnover without changing the coefficients of the two-probit model. If misconduct affects firm performance, and if boards react in the same manner as to other performance changes, the effect of misconduct on turnover would be captured simply by the model's performance term.

[37] The number of observations in Table 11 exceeds that in Table 10 as the Parrino classifications are not required for the two-probit model.

shows that misconduct does not lead to more CEO turnover at very high levels of performance. Thus, boards appear willing to forgive misconduct if firm performance is sufficiently high.

5.2 Shareholder activism and shareholder exits

We next examine two types of shareholder actions that, based on prior studies, are associated with increases in CEO turnover: shareholder activism and exits by institutional investors. Activist campaigns are often motivated by disagreements with management and frequently lead to major changes in corporate strategy or governance, including changes in the top management team (Brav, Jiang, Partnoy, and Thomas 2008; Brav, Jiang, and Kim 2014; Fos 2015). However, shareholder activism is rare, and many institutional investors use exit, rather than voice, to express their disagreement with managers' actions (Hirschman 1970; Bhide 1993; Maug 1998; Admati and Pfleiderer 2009; Edmans 2009). We therefore use large declines in firms' institutional ownership as a second indicator of shareholders' unhappiness and likely predictor of executive turnover (Parrino, Sias, and Starks 2003; Helwege, Intintoli, and Zhang 2012).[38]

Panel A of Table 12 examines firms targeted by activist shareholders. Our CEO panel includes 209 instances when an activist passes the 5% ownership threshold and files a Schedule 13D with the SEC. Panel B examines firms that suffer a one-year decline in institutional ownership of at least 10 percentage points. There are 1,698 instances in which a CEO in our sample experiences such a decline. For both shareholder events, we observe CEO turnover in the tenure year of the event and over the subsequent two years.[39]

As Table 12 shows, the CEO turnover probability increases to 18% (activism) and 17% (exits) in the event year, compared to only 12% in other years. The Parrino algorithm classifies 43% of turnovers in event years as forced, significantly more than the 21-24% in other years. Turnovers in years with shareholder events are also unusually likely to be performance induced. The two-probit model estimates this probability to be 64% (activism) and 70% (exits), which compares to only 48-52% for other years. This high rate of performance-induced turnover is no surprise as both types of events are preceded by poor performance, with 3-year industry adjusted CARs of -17% and -37%, respectively.

[38] Appendix C.2 describes the data collection for both types of events.
[39] We limit the analysis to these three years because of the small number of CEOs in later years who remain in office and have not suffered another shareholder event.

We next incorporate the shareholder events into the two-probit model, mirroring the analysis of misconduct in the previous section. Table 13 includes an event indicator in each of the two probit terms ($P_{perf-ind}$ and P_{other}) as well as an interaction of the indicator with performance in the $P_{perf-ind}$ term. The indicators identify one, two, and three-year periods starting with the event year (models (1)-(3)). Panel A examines announcements of activist campaigns, while Panel B examines large declines in institutional ownership.[40]

The results are similar to those for misconduct events. In all models, the coefficient on the event indicator in the $P_{perf-ind}$ term is positive and significant. This suggests that boards treat adverse shareholder events (or their causes) as negative signals about CEOs or, equivalently, that boards increase the threshold at which they fire CEOs. The effects are large: based on estimates from model (2), an activist event in the current or previous tenure years increases the probability of performance-induced turnover by 5.6 percentage points, from 6.3% to 11.9% per year. Institutional exits increase the probability of performance-induced turnover by 3.8 percentage points, from 6.3% to 10.1% per year.

In all models, the interaction between the event indicator and firm performance is small and insignificant. This suggests that boards do not attribute poor performance around adverse shareholder events more strongly to their CEOs than performance in other years. There is also no significant effect of shareholder events on other, not performance-induced turnover (P_{other}), which shows that shareholder events do not increase turnover at very high levels of performance.

The results in Sections 5.1 and 5.2 show that much of the increase in CEO turnover after corporate misconduct, activist campaigns, and institutional sell-offs is due to performance-induced turnovers. There is no significant increase in turnover if performance is very high. However, as performance falls, turnover increases much faster after these events than during other times, leading to the higher overall turnover rate. This pattern is consistent with the events lowering boards' assessment of CEO quality, or with boards facing increased pressure to remove underperforming CEOs. More broadly, the evidence underscores the importance of firm performance in turnover decisions.

[40] The number of observations in Table 13 exceeds that in Table 12 as the Parrino classifications are not required for the two-probit model.

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 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 and around disruptive events such as corporate scandals and activist campaigns.

The evidence also shows that performance-induced turnover is driven by recent performance, that turnover remains sensitive to performance even late in tenure, and that the rate of performance-induced turnover declines only slowly with tenure. In the context of standard Bayesian learning models of CEO turnover, this suggests that boards learn only slowly about CEO ability and act as if ability (or match quality) was subject to frequent and sizeable shocks.

Appendix A: Theoretical framework

A1: A simple Bayesian learning model of CEO turnover

This appendix describes a simple Bayesian learning model of CEO turnover. 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 $\frac{1}{r}$:

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

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:

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

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 $\underline{\alpha_t}$. Equation (A.2) shows that the board puts equal weight on each of the past performance signals when forming its estimate of CEO ability. It also shows that the sensitivity of the board's estimate of CEO ability to any performance signal declines with tenure. These are predictions (1) and (2) in Section 4.1.

A2: Extension: Changing CEO ability

We modify the simple learning model by assuming that the CEO's true ability follows a random walk:

$$\alpha_t = \alpha_{t-1} + \nu_t \quad \text{where } \nu_t \sim \mathrm{N}\left(0, \frac{1}{s}\right) \tag{A.3}$$

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

$$x_t = \alpha_t + \epsilon_t \quad \text{where } \epsilon_t \sim \mathrm{N}\left(0, \frac{1}{\mathrm{r}}\right) \tag{A.4}$$

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: [41]

$$\hat{\alpha}_1 = \frac{r}{\left(\sigma_0^2 + \frac{1}{s}\right)^{-1} + r} x_1 \tag{A.5.1}$$

$$\hat{\alpha}_2 = k_{2,1} \frac{r}{\left(\sigma_1^2 + \frac{1}{s}\right)^{-1} + r} x_1 + \frac{r}{\left(\sigma_1^2 + \frac{1}{s}\right)^{-1} + r} x_2 \tag{A.5.2}$$

$$\hat{\alpha}_3 = k_{3,2} k_{3,1} \frac{r}{\left(\sigma_2^2 + \frac{1}{s}\right)^{-1} + r} x_1 + k_{3,1} \frac{r}{\left(\sigma_2^2 + \frac{1}{s}\right)^{-1} + r} x_2 + \frac{r}{\left(\sigma_2^2 + \frac{1}{s}\right)^{-1} + r} x_3 \tag{A.5.3}$$

$$where \;\; k_{t,i} = \frac{\sigma_{t-i}^2}{\sigma_{t-i}^2 + \frac{1}{s}} \tag{A.5.4}$$

The board no longer assigns equal weights to all past signals when forming its beliefs. Instead, signals from the more distant past receive lower weights because they are less informative about current ability. This is prediction (3) in Section 4.1. 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.5.2): 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

[41] 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.*

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:

$$\sigma_t^2 = \left(\left(\sigma_{t-1}^2 + \frac{1}{s}\right)^{-1} + r\right)^{-1} \tag{A.6}$$

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.5), 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. This is prediction (4) in Section 4.1.

A3: Estimation

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. This noise term captures unmodeled determinants of the board's turnover decision, such as behavioral mistakes or transitory shocks to beliefs. Consider, for example, a CEO in tenure year *t=2* with information on performance in years t=1 and t=2 and a variable *fire* equal to one if the CEO is dismissed in year 2:

$$\tilde{\alpha}_2 = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \vartheta_2 \tag{A.7}$$

$$fire = 1 \; if \; \tilde{\alpha}_2 < \underline{\alpha}_2 \tag{A.8}$$

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, $\tilde{\alpha}_2$, and the probit coefficients correctly estimate the weights the board assigns to prior performance when assessing CEO ability. Let $P(fire = 1)$ denote the probability that a CEO in office in tenure year 2 is fired at the end of that year:

$$\begin{aligned} P(fire = 1) &= P\left(\tilde{\alpha}_2 < \underline{\alpha}_2\right) \\ &= P\left(\epsilon_2 < \underline{\alpha}_2 - \beta_0 - \beta_1 x_1 - \beta_2 x_2\right) \qquad \text{(A.9)} \\ &= \Phi(\beta_0' - \beta_1 x_1 - \beta_2 x_2) \qquad (with\ \beta_0' = \underline{\alpha}_2 - \beta_0) \end{aligned}$$

Estimating (A.9) with maximum likelihood yields consistent estimates of the weights on prior performance, both for the case with constant CEO ability in equation (A.2) and for the case with time-varying ability in equation (A.5).

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.

Appendix C: Supplementary datasets

C.1 Data on corporate misconduct

The data on corporate misconduct comes from several sources.[1] Call, Martin, Sharp, and Wilde (2018) collect a list of enforcement actions by the Security and Exchange Commission (SEC) and the Department of Justice (DOJ) from 1976 to 2012. These enforcement actions concern several provisions of the Securities Exchange Act of 1943 amended by the Foreign Corrupt Practices Act of 1977 that (broadly speaking) require issuers to keep accurate transaction records and to maintain systems of internal accounting controls. Call et al. manually compile the data from various regulatory and legal filings and other public disclosures. The dataset provided to us includes the timeline of events, including the violation period, the investigation by the DOJ or SEC, and the regulatory proceedings, but it does not include the names of implicated CEOs. Karpoff, Koester, Lee and Martin (2017) show that culpable executives often leave office before problems are made public and before any formal proceedings begin. We therefore identify potentially implicated CEOs as those in office at the end of the violation period, which is often before any public disclosures. Merging with our CEO panel and requiring data for all control variables results in 178 affected CEOs.

Our second data source is a sample of accounting restatements from 1993 to 2007 compiled by Beneish, Marshall, and Yang (2016). They combine information from SEC Accounting and Auditing Enforcement Releases, the Government Accountability Office database, and Audit Analytics. From these sources, they identify a subset of restatements related to accounting irregularities that likely represent intentional misstatements. We identify potentially implicated CEOs as those in office at the end of the restatement period. The dataset provided to us contains the names of the CEOs whose tenure overlaps with the restatement period (specifically, the authors include all CEOs from one year prior to the start of the restatement period to two years after public discovery). Matching with our sample yields 136 affected CEOs with available data.

The third dataset comes from Dyck, Morse, and Zingales (2010) and is a list of securities class action lawsuits filed from 1996 to 2004 against large U.S. corporations under the Federal

[1] We are grateful to Fabrizio Ferri, Cassandra Marshall, Gerald Martin, and Adair Morse for generously sharing their data with us.

Exchange Acts of 1933/1934. Information on the lawsuits comes from the Securities Class Action Clearinghouse at Stanford Law School. Dyck et al. include only companies with assets over $750 million and impose additional filters to minimize the inclusion of frivolous lawsuits. The dataset does not include the names of implicated CEOs. We identify potentially implicated CEOs as those in office during the alleged misconduct period. Merging with our CEO panel yields 128 affected CEOs with available data.

The final data source is the June 2007 Glass-Lewis & Co. Yellow Card Trend Alert Report, which lists firms involved in backdating scandals (see, for example, Carow, Heron, Lie, and Neal (2009) and Ertimur, Ferri, and Maber (2012)). The report includes information on whether a firm has announced an internal review, an SEC investigation, a DOJ subpoena, and other events related to option backdating during 2004 to 2007. The dataset also includes the date on which the news of the firm's involvement in backdating first appears in the press. Matching to our CEO panel yields 133 CEOs with available data who are in office on that date.

C.2 Data on institutional ownership and activist events

Institutional ownership data come from Thomson Reuters' database of 13F filings with the SEC. The dataset contains quarterly holdings of U.S. stocks and other exchange-traded securities by institutional investors with investment discretion over at least $100 million of so-called 13F securities. We make two adjustments to the data. Firstly, we adjust the holdings for stock splits that occur between the 'filing' and 'report' dates using CRSP's adjustment factors. Secondly, following Ben-David, Franzoni, and Moussawi (2016), we aggregate Blackrock's holdings, which Thompson Reuters reports under seven separate entities, into a single entity (see Lewellen and Lewellen (2018) for details). We define an institutional exit as a one-year decline in institutional ownership of at least 10 percentage points. Merging with our CEO panel results in 1,698 instances in which a CEO experiences such an event.

Our sample of activist 13D filers comes from WhaleWisdom, a data provider that collects and aggregates SEC filings. The dataset covers the period from 2003 to 2015. Based on WhaleWisdom's description, the activists in the sample include hedge funds, investment advisors, activist investors, and a small number of trusts, banks, foreign pension funds, and other investors. Merging this dataset to our CEO panel yields 209 instances when an activist passes the 5% ownership threshold and files a Schedule 13D for one of our sample firms.

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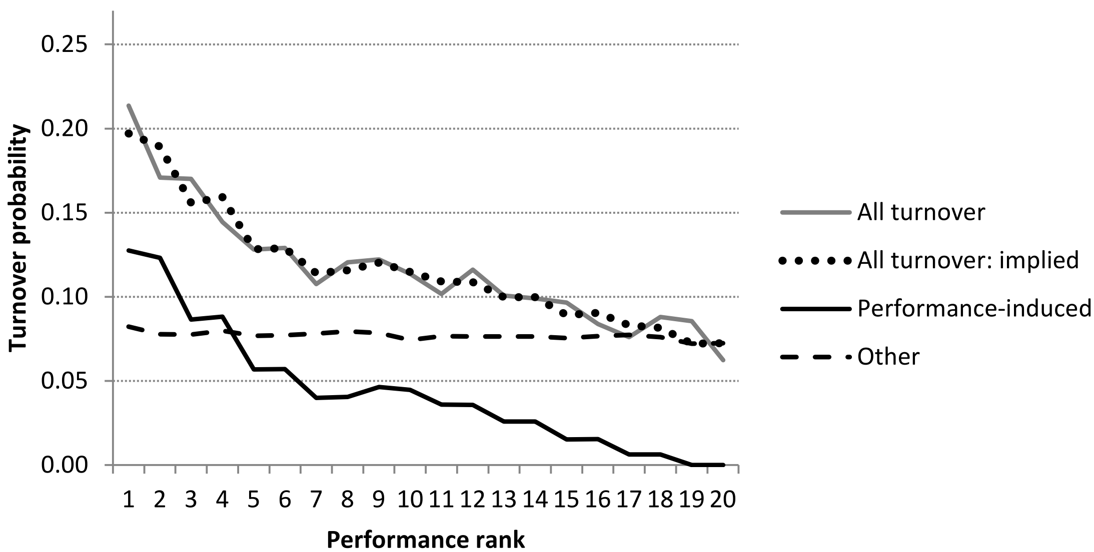
Fig. 3: Performance-induced and other turnover as a function of performance. The figures depict actual and model-implied CEO turnover probabilities as a function of performance. Implied turnover probabilities are from a probit model with performance decile indicators (3.a) and a two-probit model (3.b).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

3.a: Probit with performance-decile indicators



3.b: Two-probit model

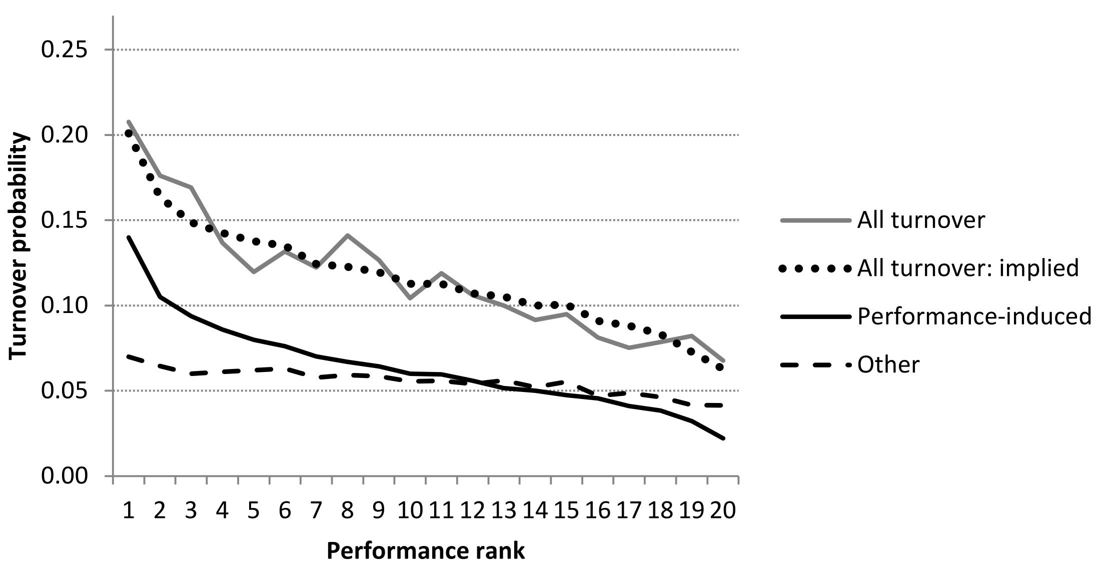
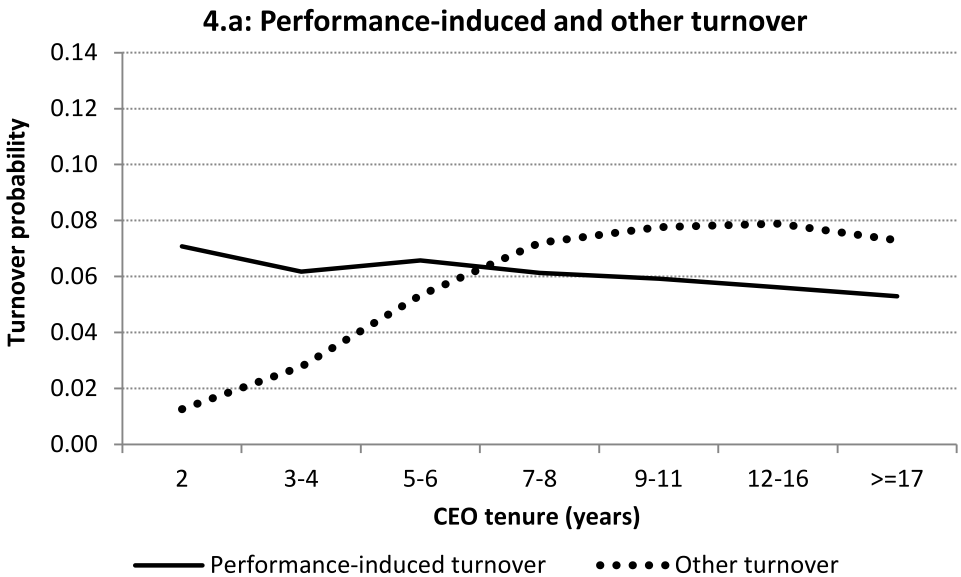


Fig. 4: Turnover probabilities as a function of CEO tenure. The figures show model-implied turnover probabilities as a function of CEO tenure. Implied probabilities of performance-induced and other turnover (4.a) are from the two-probit model in Table 8. Implied probabilities of forced and voluntary turnover (4.b) are from the standard probit model in Table 9. Implied probabilities are calculated for each observation (leaving all variables at their actual values) and then averaged within tenure bins.



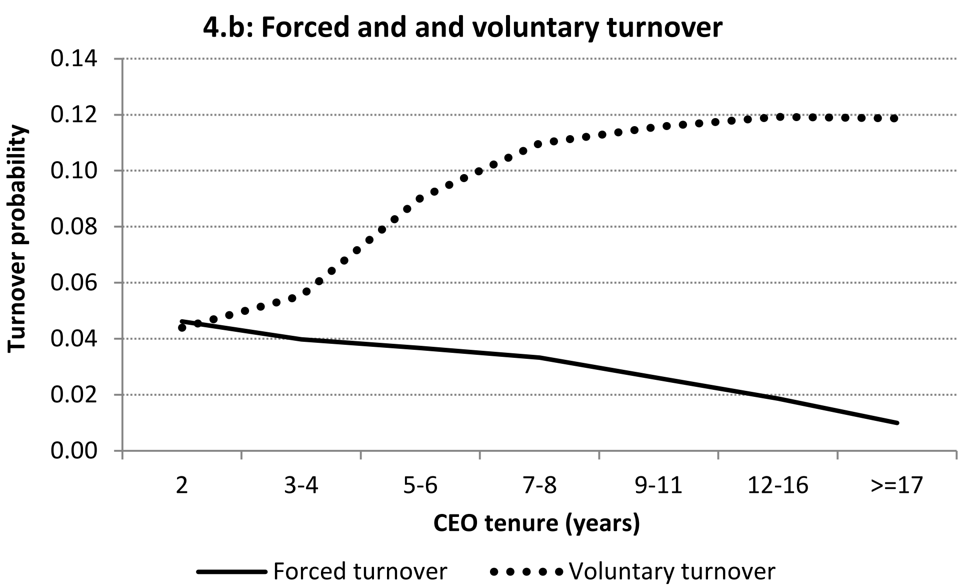


Table 1: Estimating performance-induced turnover: Simulations. The table shows descriptive statistics for estimates from 500 randomly generated samples of 23,000 CEO-years each. In the simulations, performance-induced departures occur with probability $P_{perf-ind} = \Phi(\beta_1 + \beta_2 \cdot x_t)$, 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. (6). The turnover-performance relation $P_{turn}(x_t)$ is estimated using a standard probit model with decile dummies (eq. (4)) or the two-probit model (eq. (5)), 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. (3), 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. (5)). 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, 4,963 CEO-spells, 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 industry-adjusted 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 (3)). *, **, 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 industry-adjusted 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 $P_{perf-ind}$ term. The probability of "other turnover" is calculated as the implied probability of the P_{other} 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.**
$\mathbf{P_{perf-ind}}$:								
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]
$\mathbf{P_{other}}$:								
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		
5th percentile	18.21%	18.53%	19.04%	19.23%
15th percentile	15.03%	15.08%	15.58%	15.97%
25th percentile	13.48%	13.45%	14.01%	14.50%
35th percentile	12.41%	12.35%	12.93%	13.47%
45th percentile	11.53%	11.46%	12.07%	12.60%
55th percentile	10.79%	10.71%	11.29%	11.81%
65th percentile	10.09%	9.99%	10.59%	11.10%
75th percentile	9.37%	9.26%	9.83%	10.32%
85th percentile	8.61%	8.48%	9.01%	9.45%
95th percentile	7.54%	7.40%	7.86%	8.19%
All	11.66%	11.65%	12.19%	12.68%
		Performance-induced turnover		
5th percentile	13.30%	13.32%	13.65%	14.08%
15th percentile	9.95%	9.69%	9.99%	10.63%
25th percentile	8.32%	7.97%	8.33%	9.06%
35th percentile	7.20%	6.82%	7.18%	7.98%
45th percentile	6.27%	5.87%	6.28%	7.06%
55th percentile	5.50%	5.08%	5.45%	6.22%
65th percentile	4.76%	4.33%	4.71%	5.47%
75th percentile	4.00%	3.56%	3.91%	4.64%
85th percentile	3.21%	2.74%	3.05%	3.73%
95th 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: Comparing forced and performance-induced turnovers. Turnovers are classified as performance induced using implied probabilities from two-probit model (2) in Table 4. All turnovers for which the implied probability of being performance induced is higher than 50% are labeled as "performance induced," all other turnovers as "not performance induced." This implied probability is calculated as the probability of a performance-induced turnover given that a turnover has occurred: Prob(performance-induced turnover | turnover) = Prob(performance-induced turnover) / Prob(turnover). Forced turnovers are identified using the Parrino (1997) algorithm described in Appendix B.

Panel A: Turnovers classified as forced or performance induced

	Performance induced	Not performance induced	Total
Forced	506 (82%)	113 (18%)	619
Voluntary	794 (41%)	1147 (59%)	1941
Total	1,300 (51%)	1,260 (49%)	2,560

Panel B: CEO and firm characteristics by turnover classification

Forced / Perf.-Induced:	Yes/Yes		Yes/No		No/Yes		No/No	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Log assets	6.9	6.8	9.2	9.3	6.6	6.5	8.1	8.0
Dividend payer	0.41	0.00	0.95	1.00	0.30	0.00	0.92	1.00
ROA	0.14	0.13	0.12	0.12	0.17	0.17	0.16	0.14
3-year CAR	-47%	-45%	0%	4%	-12%	-17%	12%	7%
CEO age	52.5	53.0	59.4	59.0	56.4	57.0	63.7	64.0
Age 61-63	0.03	0.00	0.20	0.00	0.12	0.00	0.29	0.00
Age 64-66	0.00	0.00	0.12	0.00	0.04	0.00	0.33	0.00
Age >66	0.01	0.00	0.08	0.00	0.10	0.00	0.18	0.00
Tenure	7.1	6.0	10.4	7.0	10.5	9.0	12.6	10.0
Obs.	506	506	113	113	794	794	1,147	1,147

Table 6: 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 industry-adjusted 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		
5th percentile	7.25%	7.51%	7.24%	6.73%
15th percentile	4.82%	4.85%	4.63%	4.29%
25th percentile	3.74%	3.69%	3.54%	3.27%
35th percentile	3.03%	2.95%	2.84%	2.60%
45th percentile	2.49%	2.41%	2.33%	2.14%
55th percentile	2.06%	1.97%	1.90%	1.73%
65th percentile	1.68%	1.57%	1.53%	1.37%
75th percentile	1.31%	1.20%	1.17%	1.04%
85th percentile	0.95%	0.81%	0.79%	0.71%
95th percentile	0.51%	0.38%	0.37%	0.33%
All	2.83%	2.83%	2.70%	2.50%

Table 7: 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 industry-adjusted 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 8: 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 industry-adjusted 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.

$\mathbf{P_{perf-ind}}$:		
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]

$\mathbf{P_{other}}$:		
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 9: 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 industry-adjusted 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			cont.		
Tenure year 2			Tenure (3,4)	-0.0888	[-1.53]
Scaled return t=0	-0.219***	[-4.96]	Tenure (5,6)	-0.0843	[-1.35]
Scaled return t=-1	-0.208***	[-4.59]	Tenure (7,8)	-0.120	[-1.69]
Tenure years 3-4			Tenure (9-11)	-0.198**	[-2.74]
Scaled return t=0	-0.242***	[-6.17]	Tenure (12-16)	-0.373***	[-4.66]
Scaled return t=-1	-0.317***	[-8.27]	Tenure (17+)	-0.425***	[-4.90]
Scaled return t=-2	-0.113**	[-3.19]	Age	-0.00608	[-1.71]
Tenure years 5-6			Age 61-63	-0.408***	[-4.91]
Scaled return t=0	-0.175***	[-4.01]	Age 64-66	-0.486***	[-3.75]
Scaled return t=-1	-0.348***	[-7.39]	Age > 66	-0.343**	[-2.63]
Scaled return t=-2	-0.150***	[-3.50]	Dividend	-0.311***	[-7.47]
Tenure years 7-8			Log assets	0.0102	[0.82]
Scaled return t=0	-0.219***	[-4.24]	Constant	-1.298***	[-6.84]
Scaled return t=-1	-0.349***	[-5.87]	N	22,887	
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]			

Table 10: CEO turnover following corporate misconduct. The table shows descriptive statistics for CEO turnover during the five tenure years starting with the year in which the corporate misconduct ends. The misconduct events are described in Appendix C.1. Forced turnovers is the proportion of turnovers classified as forced using the Parrino (1997) algorithm described in Appendix B. Prob. perf.-induced is the average probability that a given turnover is performance induced calculated using implied probabilities from two-probit model (2) in Table 4. This probability is calculated as: Prob(performance-induced turnover | turnover) = Prob(performance-induced turnover) / Prob(turnover). 3-year industry-adj. CARs are average cumulative industry-adjusted monthly stock returns over tenure years [-2,0], with the CEO turnover in tenure year 0.

Panel A: CEO turnover rates in the five years following corporate misconduct

Misconduct type	Tenure years	Turnover probability
Enforcement action	396	0.25
Backdating	326	0.16
Lawsuits	297	0.26
Restatements	336	0.24
All misconduct	1,122	0.21
No misconduct	19,313	0.12

Panel B: CEO turnovers in the five years following corporate misconduct

Misconduct type	Turn-overs	Forced turnovers	Prob. perf.-induced	3-year industry-adj. CARs	CEO age
Enforcement action	100	0.51	0.60	-0.28	57.3
Backdating	51	0.55	0.74	-0.16	54.9
Lawsuits	77	0.55	0.59	-0.47	55.5
Restatements	79	0.47	0.70	-0.31	55.0
All misconduct	231	0.49	0.63	-0.28	56.2
No misconduct	2,329	0.22	0.51	-0.05	59.3

Table 11: Performance-induced turnover after corporate misconduct. The table shows two-probit regressions of an indicator for CEO turnover on firm performance, a misconduct indicator for the period from the tenure year in which corporate misconduct ends to one year (model (1)) to four years (model (4)) later, and controls. Performance is measured as average industry-adjusted monthly stock returns scaled by the standard deviation of returns. Returns are measured over tenure years [-2,0], with year 0 the year of the CEO turnover. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

	(1)		(2)		(3)		(4)	
	Coefficient	T-stat.	Coefficient	T-stat.	Coefficient	T-stat.	Coefficient	T-stat.
Post-misconduct period:	**2 years**		**3 years**		**4 years**		**5 years**	
$\mathbf{P_{perf-ind}}$:								
Misconduct	**0.590*** **	**[6.37]**	**0.522*** **	**[6.02]**	**0.473*** **	**[5.82]**	**0.445*** **	**[5.46]**
Scaled return t=[-2, 0]	-0.289***	[-6.44]	-0.289***	[-6.50]	-0.298***	[-6.84]	-0.297***	[-6.83]
Scaled return t=[-2, 0] * Miscond.	**-0.0079**	**[-0.12]**	**0.0117**	**[0.19]**	**0.00988**	**[0.17]**	**-0.00883**	**[-0.15]**
Age	0.0101	[1.57]	0.00992	[1.54]	0.00905	[1.45]	0.00875	[1.41]
Tenure	-0.00829*	[-2.14]	-0.00807*	[-2.10]	-0.00855*	[-2.17]	-0.00879*	[-2.18]
Dividend	-0.361***	[-4.90]	-0.348***	[-4.61]	-0.364***	[-5.37]	-0.359***	[-5.25]
Log assets	-0.0354*	[-2.01]	-0.0381*	[-2.15]	-0.0413*	[-2.29]	-0.0423*	[-2.33]
Constant	-1.583***	[-4.17]	-1.566***	[-4.10]	-1.506***	[-4.11]	-1.485***	[-4.06]
$\mathbf{P_{other}}$:								
Misconduct	**-0.159**	**[-0.37]**	**-0.0775**	**[-0.25]**	**0.0264**	**[0.14]**	**-0.0397**	**[-0.22]**
Age	0.0392***	[4.59]	0.0403***	[4.88]	0.0402***	[5.03]	0.0401***	[5.03]
Age 61-63	0.454***	[3.71]	0.451***	[3.73]	0.431***	[4.16]	0.434***	[4.15]
Age 64-66	0.914***	[4.85]	0.908***	[4.88]	0.876***	[5.53]	0.878***	[5.49]
Age > 66	0.369*	[1.97]	0.353	[1.95]	0.334*	[2.05]	0.340*	[2.07]
Tenure	-0.0109**	[-2.71]	-0.0112**	[-2.78]	-0.0108**	[-2.87]	-0.0107**	[-2.84]
Dividend	0.408*	[2.35]	0.394*	[2.32]	0.387*	[2.31]	0.375*	[2.30]
Log assets	0.0738***	[4.65]	0.0751***	[4.56]	0.0721***	[4.84]	0.0730***	[4.86]
Constant	-4.904***	[-9.75]	-4.968***	[-9.82]	-4.899***	[-10.14]	-4.889***	[-10.21]
N	23,399		23,399		23,399		23,399	

Table 12: CEO turnover following shareholder activism and exits. The table shows descriptive statistics for CEO turnover during the three tenure years starting with the year of a shareholder event. In Panel A, a shareholder event is the first filing of a 13D form by an activist investor; in Panel B, an event is a one-year decline in institutional ownership of at least 10 percentage points. The shareholder events are described in Appendix C.2. Forced turnovers is the proportion of turnovers classified as forced using the Parrino (1997) algorithm described in Appendix B. Prob. perf.-induced is the average probability that a given turnover is performance induced calculated using implied probabilities from two-probit model (2) in Table 4. This probability is calculated as: Prob(performance-induced turnover | turnover) = Prob(performance-induced turnover) / Prob(turnover). 3-year industry-adj. CARs are average cumulative industry-adjusted monthly stock returns over tenure years [-2,0], with the CEO turnover in tenure year 0.

Observation period	Tenure years	Turnover probability	Turnovers	Forced turnovers	Prob. perf.-induced	3-year industry-adj. CARs
Panel A: Activist campaigns						
1 year	209	0.18	37	0.43	0.64	-0.17
2 years	319	0.17	55	0.36	0.64	-0.15
3 years	365	0.18	64	0.34	0.60	-0.12
Other years	20,070	0.12	2,496	0.24	0.52	-0.07
Panel B: Large declines in institutional ownership						
1 year	1,698	0.17	295	0.43	0.70	-0.37
2 years	2,751	0.16	439	0.39	0.68	-0.29
3 years	3,386	0.16	528	0.37	0.68	-0.28
Other years	17,049	0.12	2,032	0.21	0.48	-0.02

Table 13: Performance-induced turnover after shareholder activism and exits. Panels A and B show two-probit regressions of an indicator for CEO turnover on firm performance, an indicator for the period from the tenure year of a shareholder event (model (1)) to two (model (3)) years later, and controls. In Panel A, a shareholder event is a 13D filing by an activist investor; in Panel B it is a one-year decline in institutional ownership of at least 10 percentage points. Performance is measured as average industry-adjusted monthly stock returns scaled by the standard deviation of returns. Returns are measured over tenure years [-2,0], with year 0 the year of the CEO turnover. *, **, and ** denote significance at the 5%, 1%, and 0.1% level, respectively.

Panel A: Activist campaigns

	(1)		(2)		(3)	
	Coefficient	T-stat.	Coefficient	T-stat.	Coefficient	T-stat.
Post-activism period:	**1 year**		**2 years**		**3 years**	
$\mathbf{P_{perf-ind}}$:						
Activism	**0.225**	**[1.44]**	**0.366*** **	**[3.34]**	**0.314** **	**[2.90]**
Scaled return t=[-2, 0]	-0.297***	[-7.71]	-0.297***	[-8.17]	-0.295***	[-7.89]
Scaled return t=[-2, 0] * Activism	**0.0352**	**[0.30]**	**0.000769**	**[0.01]**	**-0.0147**	**[-0.18]**
Age	0.00902	[1.49]	0.00873	[1.52]	0.0088	[1.48]
Tenure	-0.00716*	[-2.02]	-0.00740*	[-2.10]	-0.00720*	[-2.01]
Dividend	-0.402***	[-6.18]	-0.396***	[-6.43]	-0.395***	[-6.25]
Log assets	-0.027	[-1.69]	-0.0288	[-1.85]	-0.0282	[-1.79]
Constant	-1.557***	[-4.50]	-1.536***	[-4.71]	-1.544***	[-4.56]
$\mathbf{P_{other}}$:						
Activism	**-0.164**	**[-0.47]**	**-0.424**	**[-1.47]**	**-0.299**	**[-1.22]**
Age	0.0381***	[4.51]	0.0380***	[4.49]	0.0380***	[4.46]
Age 61-63	0.449***	[4.18]	0.455***	[4.44]	0.455***	[4.27]
Age 64-66	0.908***	[5.57]	0.909***	[5.93]	0.914***	[5.65]
Age > 66	0.377*	[2.16]	0.384*	[2.24]	0.387*	[2.20]
Tenure	-0.0112**	[-2.93]	-0.0110**	[-2.99]	-0.0112**	[-2.94]
Dividend	0.446*	[2.48]	0.435**	[2.62]	0.439*	[2.54]
Log assets	0.0700***	[5.00]	0.0711***	[5.11]	0.0710***	[5.07]
Constant	-4.828***	[-10.34]	-4.818***	[-10.44]	-4.822***	[-10.43]
N	23,399		23,399		23,399	

Panel B: Large declines in institutional ownership

	(1)		(2)		(3)	
	Coefficient	T-stat.	Coefficient	T-stat.	Coefficient	T-stat.
Post-decline period:	**1 year**		**2 years**		**3 years**	
$\mathbf{P_{perf-ind}}$:						
Ownership decline	**0.303*** **	**[5.21]**	**0.257*** **	**[5.21]**	**0.255*** **	**[5.06]**
Scaled return t=[-2, 0]	-0.259***	[-6.47]	-0.261***	[-6.39]	-0.255***	[-5.71]
Scaled return t=[-2, 0] * Decline	**-0.0651**	**[-1.41]**	**-0.0511**	**[-1.24]**	**-0.06**	**[-1.45]**
Age	0.0116	[1.87]	0.0117	[1.91]	0.012	[1.93]
Tenure	-0.00643	[-1.90]	-0.00752*	[-2.07]	-0.00824*	[-2.10]
Dividend	-0.368***	[-5.16]	-0.367***	[-5.36]	-0.347***	[-4.98]
Log assets	-0.0148	[-0.95]	-0.0164	[-1.03]	-0.0172	[-1.01]
Constant	-1.798***	[-5.00]	-1.803***	[-5.00]	-1.820***	[-4.92]
$\mathbf{P_{other}}$:						
Ownership decline	**-0.0892**	**[-0.50]**	**-0.0533**	**[-0.43]**	**-0.109**	**[-0.93]**
Age	0.0397***	[4.37]	0.0385***	[4.34]	0.0371***	[4.08]
Age 61-63	0.482***	[3.59]	0.479***	[3.80]	0.492***	[3.53]
Age 64-66	0.961***	[4.66]	0.955***	[4.92]	0.977***	[4.55]
Age > 66	0.385	[1.88]	0.385*	[1.98]	0.421*	[2.00]
Tenure	-0.0122**	[-2.71]	-0.0111**	[-2.58]	-0.0108*	[-2.42]
Dividend	0.513*	[2.40]	0.506*	[2.37]	0.482*	[2.34]
Log assets	0.0687***	[4.60]	0.0702***	[4.77]	0.0718***	[4.84]
Constant	-5.030***	[-9.46]	-4.965***	[-9.40]	-4.887***	[-9.46]
N	23,399		23,399		23,399	