Reputation and Investor Activism: 
A Structural Approach

Online Appendix

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Abstract

We provide additional analyses detailing the construction of our campaign outcome propensity measures, comparing the predictive value and persistence of measures of activists’ idea quality to measures of aggressiveness, deriving standard errors that account for estimation error in \( \sigma_{car} \) and \( \beta_i \), re-estimating our model under a variety of alternative assumptions, examining the relation between our measure of reputation and long-term target stock returns, comparing a sample of non hedge fund activists to our main sample of hedge fund activists, and detailing how to compute our reputation measure in future research.

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Appendix A. Construction of campaign outcome propensity measures

Appendix C of the paper outlines the construction of \( \hat{a}_i \), our estimate of the likelihood action \( i \) would occur in a certain firm-year in the absence of an activist campaign. We calculate \( \hat{a}_i \) for each campaign as the fitted value from a cross-sectional regression predicting future corporate actions using observables during the quarter \( t \) when the campaign is initiated. We estimate this regression on a wider sample that includes all publicly traded firms in the intersection of the CRSP and Compustat panels. Equation (1) outlines each regression:

\[
a_{j,i,t+4} = \alpha_{i,t} + \gamma_{i,t} \cdot X_{j,t} + \epsilon_{j,i,t+4},
\]

where \( a_{j,i,t+4} \) is action indicator \( i \) (one of Reorg, Payout, CEO, Board, and Acq) measured in the year following quarter \( t \) for firm \( j \), and \( X_{j,t} \) is a vector of company characteristics measured in quarter \( t \): Log Size\(_{j,t} \), EBIT/Assets\(_{j,t} \), Net Leverage\(_{j,t} \), Payout/Assets\(_{j,t} \), Capex/Assets\(_{j,t} \), Book to Market\(_{j,t} \), Inst Ownership\(_{j,t} \), and 1-Year Return\(_{j,t} \).

Online Appendix Table 1 shows the average coefficients across each of our 56 quarterly cross-sectional predictive regressions, with \( t \)-statistics calculated using the cross-quarter standard deviations in coefficients in a manner similar to Fama and MacBeth (1973).

Appendix B. Variation in idea quality across activists

A natural alternative model is one in which activists differ by the quality of their ideas (\( \Delta \) in the model) rather than their aggressiveness (\( \mu_A \)). In this setting, reputation would be an estimate of the activists’ idea quality based on their past campaigns.

We disentangle these alternative models by empirically assessing the extent to which measures of an activists’ idea quality and aggressiveness are persistent and predict campaign frequency and success. We find that measures of aggressiveness are both predictive and persistent within activist, while measures of idea quality have no predictive power and are not persistent. These results suggest differences across activists in aggressiveness are more

\footnote{We define in detail how we calculate each of the actions and characteristics in Appendix B.}
important drivers of observable behavior than differences in idea quality.

First, we estimate the ability of measures for past aggressiveness and idea quality to predict how target firms and the stock market respond to future campaigns. We measure aggressiveness using \textit{PastProxy}, the fraction of prior campaigns by the activist with a proxy fight. Online Appendix Table 2 shows that \textit{Past Proxy} strongly predicts market reactions to future campaigns (\textit{CAR}) and the number of abnormal activist-friendly actions taken by targets (\textit{Ab Actions}) in non-proxy campaigns.\footnote{We also find mixed evidence past \textit{Ab Actions} and past campaign frequency, the two other variables affecting \( r_t \) in our model, predict responses to future campaigns.}

The ideal measure for an activists’ idea quality would be their targets’ long-run abnormal stock returns in successful campaigns. Unfortunately, as discussed in Section 4.1 of the paper, we do not directly observe campaign success, and instead only observe indicators for proxy fights (\textit{Proxy}) and activist-friendly actions (a). We therefore estimate an activists’ idea quality using three related measures:

1. \textit{PastCAR}_{250} | \textit{Proxy}, average \textit{CAR}_{250} in the activist’s past campaigns with \textit{Proxy} = 1, where \textit{CAR}_{250} is the target’s cumulative abnormal return from 10 trading days prior to the campaign announcement to 250 trading days after.

2. \textit{PastCAR}_{250} | \textit{HiAct}, average \textit{CAR}_{250} in the activist’s past campaigns with \textit{Ab Actions} above the full-sample median.

3. \textit{Past CAR}_{250}, average \textit{CAR}_{250} in all the activist’s past campaigns.

Online Appendix Table 2 shows that none of these measures for activist-specific idea quality predict future abnormal target actions or campaign announcement returns.

Our second approach to disentangling reputation for idea quality from reputation for aggression is to test whether measures for each are persistent within activist, a necessary condition for reputation to be important. We do so by estimating regressions of the form:

\[
x_c = a + \rho \cdot \text{Past } \bar{x}_c + \epsilon_c,
\]

where \( x_c \) is a measurable outcome of campaign \( c \) and \text{Past } \bar{x}_c \) is the average value of \( x_c \)
in prior campaigns by the activist initiating campaign $c$. The outcome variables we use are $Proxy$, $AbActions$, $13-D$, $CAR_3$, $CAR_{250}|Proxy$, $CAR_{250}|HiAct$, and $CAR_{250}$, each defined above. The results, in Panel C of Online Appendix Table 2, show that proxy fighting, target actions, campaign frequency, and campaign announcement returns are all persistent within-activist, suggesting that activist types vary across these dimensions. By contrast, we find that none of the measures of idea quality are persistent within activist.

Given the noise in year-long abnormal returns, the evidence in Online Appendix Table 2 that return-based measures of idea quality are not predictive or persistent does not conclusively rule out the possibility of differences in idea quality across activists. However, we argue this noise is precisely what makes it difficult for targets to learn about activists’ average idea quality. Learning about aggressiveness, by contrast, is much more direct and therefore much more amenable to reputation effects in practice, as illustrated by the results in Online Appendix Table 2. For these reasons, our model focuses on activist types differing by aggressiveness rather than idea quality.

Appendix C. Standard errors and confidence intervals

C.1. Standard errors

As described in Section 4, we fix some parameters exogenously ($\Omega$) and estimate the remaining parameters ($\theta$) using maximum likelihood. For six of the exogenous parameters, $\sigma_{car}$ and $\beta_i$ for the five target actions $i$, the values we fix are from reduced form regressions. We therefore need to account for first-stage estimation error in these reduced form regressions when computing standard errors for $\theta$. To do so, we combine our reduced-form estimations of $\sigma_{car}$ and $\beta_i$ with our maximum likelihood estimation of the remaining parameters into a one-stage method-of-moments estimation. As described in Section 4.3, we estimate $\sigma_{car}$ as the standard deviation of $CAR_c$ in our sample and $\beta_i$ as the average ‘unexpected’ value of
an indicator for action $i$ ($a_i - \hat{a}_i$) in campaigns with a proxy fight. Defining:

$$\Theta \equiv \begin{bmatrix} \sigma_{car} & \beta & \theta \end{bmatrix}',$$

we can therefore combine our estimations of $\sigma_{car}$ and $\beta_i$ with our maximum-likelihood estimation of $\theta$ into a unified method of moments estimator solving:

$$\frac{1}{N} \sum_{c=1}^{N} m_c(\Theta) = 0,$$

where $N$ is the number of campaigns and the moment conditions $m_c$ are:

$$m_c(\Theta) = \begin{bmatrix} (CAR_c - \overline{CAR})^2 - \sigma^2_{car} \\ (a_{1,c} - \hat{a}_{1,c} - \beta_1)(Proxy = 1) \\ \vdots \\ (a_{5,c} - \hat{a}_{5,c} - \beta_3)(Proxy = 1) \end{bmatrix},$$

with $L_c(\theta)$ defined as the conditional likelihood function for campaign $c$ given in Equation (22). This moment-based approach produces the same estimates of $\Theta$ we get from separately estimating $\sigma^2_{car}$, $\beta$, and $\theta$ but allows us to compute standard errors for $\Theta$ which account for estimation error in $\hat{\sigma}^2_{car}$ and $\hat{\beta}$ using the standard method of moments asymptotic results.

$$\sqrt{N}(\hat{\Theta} - \Theta_0) \sim N \left[ 0, A^{-1}BA'^{-1} \right].$$

---

3In principle, we have enough independent variation across different outcome variables to estimate the full parameter vector $\Theta$ using maximum likelihood. We choose not to because finding a global maximum with 16 independent variables ($\sigma^2_{car}$, five $\beta_i$, and ten $\theta_i$) is computationally challenging, and because we have relatively direct and low-noise estimates of $\beta$ and $\sigma_{car}$.

4Note that this estimator is just-identified because there are 16 total parameters and 16 moments, so we do not have to use a GMM weighting matrix.
where the matrices $A$ and $B$ using:

$$\hat{A} = \frac{1}{N} \sum_{c=1}^{N} \frac{\partial m_c(\Theta)}{\partial \Theta^t},$$

(7)

$$\hat{B} = \frac{1}{N} \sum_{c=1}^{N} \sum_{d=1}^{N} m_c(\Theta)m_d(\Theta)^t \cdot 1 \text{ (c and d initiated by same activist).}$$

(8)

Notice we specify the moment covariance estimator $B$ to sum across all pairs of campaigns by the same activist, effectively clustering our standard errors by activist.

C.2. Confidence intervals

The confidence intervals we compute are based on likelihood ratio tests. The likelihood ratio test for any hypotheses constraining $\theta$ to be in set $\Theta_{alt}$ computes the test statistic:

$$\Lambda(\Theta_{alt}) = 2 \log \left( \frac{L(\hat{\theta})}{\sup_{\theta \in \Theta_{alt}} L(\theta)} \right),$$

(9)

which has an asymptotic $\chi^2$ distribution with $k$ degrees of freedom, where $k$ is the number of constrained dimensions in $\Theta_{alt}$. Informally, $\Lambda$ measures how much less likely the data is when $\theta$ is constrained relative to the unconstrained maximum.

We form confidence intervals for parameter $i$, $[LB_i, UB_i]$, using likelihood ratio tests as follows:

$$LB_i = \inf \left\{ \underline{\theta}_i \text{ s.t. } \Lambda(\{ \theta \text{ s.t. } \theta_i = \underline{\theta}_i \}) \leq \chi^2(0.975, 1) \right\},$$

(10)

$$UB_i = \sup \left\{ \bar{\theta}_i \text{ s.t. } \Lambda(\{ \theta \text{ s.t. } \theta_i = \bar{\theta}_i \}) \leq \chi^2(0.975, 1) \right\},$$

(11)

where $\chi(0.975, 1)$ equals the 97.5% $\chi^2$ critical value with one degree of freedom.

Intuitively, these confidence intervals represent the set of $\theta_i$ for which if we re-estimate the model with a restriction that parameter $i$ equals $\theta_i$, the decline in the maximum attainable likelihood is sufficiently small relative to the unconstrained maximum likelihood. For values of parameter $i$ outside the 95% confidence intervals, we cannot fit the data as well as our point estimate does regardless of how we adjust the values of the other nine parameters in $\theta$. Compared to the standard errors described above, these confidence intervals have
the advantage of producing more-powerful tests and using information about the likelihood function’s shape away from our point estimates. The disadvantage of this approach is it ignores any estimation error in $\sigma_{car}$ and $\beta_i$.

Appendix D. Identification

D.1. Plots for all comparative statics and empirical predictions

As discussed in Section 3.6 of the paper, our maximum likelihood estimation identifies model parameters if and only if each parameter impacts our model’s empirical predictions in a way that cannot be duplicated by any combination of other parameters. Figures 3 and 4 illustrate each parameter’s main effect on equilibrium strategies and the empirical predictions, respectively. We provide evidence these effects are unique in Table 3 using the local elasticities of model-implied moments to changes in parameters.

As an additional illustration that no two parameters have the same impact on equilibrium outcomes, Online Appendix Figures 1 and 2 plot all the combinations of comparative statics and empirical predictions presented in the paper with all model parameters. To facilitate comparison, each page of plots contains the effect of increasing each of the ten parameters (holding other parameters fixed) on a specific strategy or empirical prediction.

Online Appendix Figure 2 also plots the relations between model parameters and two empirical predictions which we reference in Section 3.6 but do not plot in Figure 4. Panel F shows how $r_t$ decays when starting at 99% on day $t = 0$ if no observed campaigns occur. The arrival rate of type resets $\lambda_r$ primarily affects the shape of this plot, meaning we identify $\lambda_r$ using campaigns by activists after with long idle periods.

Panel G of Online Appendix Figure 2 shows how changing model parameters affects the expected target announcement return, $CAR$. Because predicted $CAR$ satisfies:

$$
E(CAR) = \Delta \cdot (P(Settle) + P(Fight)),
$$

(12)

$E(CAR)$ offers no unique empirical predictions not offered by $P(Settle)$ and $P(Fight)$ for
any parameter except $\Delta$. It is still useful to ask our estimation to fit observed \textit{CAR} for two reasons: it allows us to identify $\Delta$ using the ratio of average observed \textit{CAR} to average observed \textit{Settle + Fight}, and it yields additional variation for the model to match, effectively making our estimation ‘over-identified’ in the sense that no single set of parameters can fit all the dimensions of observed data perfectly.

The main conclusions from the plots in Online Appendix Figures 1 and 2 are that each parameter has a substantial impact on at least one empirical prediction in our sample, and that no two parameters have the same or proportional effects on these observed predictions. We can therefore identify model parameters using our maximum likelihood approach given sufficient data.


Andrews, Gentzkow, and Shapiro (2017) proposes new a measure to help understand identification in structural estimation which answers the question: how much would parameter estimates change if moments in the data change? This metric is very intuitive and useful for estimators based on matching a specified set of moments, for example the simulated method of moments (SMM). While it can also be computed for maximum likelihood estimators (MLEs), it is more-difficult to interpret because MLE does not directly use a specific set of moments. Instead, the ‘moments’ in MLE are the partial derivatives of the log likelihood function with respect to the parameters:

\[ \hat{g} (\theta) = \hat{\mathbb{E}} \left( \frac{\partial \log (L_c(\theta))}{\partial \theta} \right), \tag{13} \]

where $\hat{\mathbb{E}}$ is the sample average and $L_c(\theta)$ is the likelihood of campaign $c$ given parameters $\theta$.

To apply the moment equation (13) in the Andrews, Gentzkow, and Shapiro (2017), we need to specify the weighting matrix $W$. Because MLE finds the $\hat{\theta}$ for which each of these partial derivatives is exactly zero, we can use identity matrix as the weighting matrix $W$. 

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The Andrews, Gentzkow, and Shapiro (2017) sensitivity measure then becomes:

\[
\hat{\Lambda} = -(\hat{G}'\hat{G})^{-1}\hat{G}' = -\hat{G}^{-1},
\]

(14)

\[
\hat{G} \equiv \frac{\partial \hat{g}(\theta)}{\partial \theta'} = \hat{E}\left(\frac{\partial^2 \log(L_c(\theta))}{\partial \theta \partial \theta'}\right).
\]

(15)

Combining equations (14) and (15), we see that the Andrews, Gentzkow, and Shapiro (2017) measure for MLE is the negative inverse of the Hessian matrix, which standard results (e.g., in Cameron and Trivedi (2005)) show equals the variance of parameter estimates:

\[
Var(\hat{\theta}_{MLE}) = -(\hat{E}\left(\frac{\partial^2 \log(L_c(\theta))}{\partial \theta \partial \theta'}\right))^{-1} = -\hat{G}^{-1} = \hat{\Lambda}.
\]

(16)

The square roots of the diagonal elements of $Var(\hat{\theta}_{MLE})$ are the standard errors for $\theta_{MLE}$, which we estimate using the procedure in Online Appendix C and present in Table 2.

We present the non-diagonal elements of $\hat{\Lambda} = Var(\hat{\theta}_{MLE})$, scaled to a correlation matrix, in Online Appendix Table 3. The correlation between parameters $\theta_i$ and $\theta_j$ can be interpreted as the extent to which they are complements (positive correlation) or substitutes (negative correlation) in fitting the observed data. For example, the largest absolute correlation we find is between $\tau_L$ and $d_{caut,0}$ (-0.84), which implies that we can fit the model almost as well by increasing $d_{caut,0}$ and decreasing $\tau_L$, or vice-versa. This substitutability comes from the fact that both $\tau_L$ and $d_{caut,0}$ are strongly positively related to the average arrival rate of campaigns (13-D), as illustrated by Table 3, one of the most precisely-measured moments in the data. Still, the two are far from perfectly correlated, and we can separate them using the fact that $\tau_L$ is much more strongly related to the difference in campaign frequency between high and low $r_t$.

The other two strong correlations in Online Appendix Figure 3 are between $\Delta$ and $y_0$, and $\Delta$ and $f_{caut,0}$. These arise because all three variables have substantial impact on the average $CAR$, as illustrated by Table 3 and Online Appendix Figure 2. We can nevertheless separately identify these three parameters, making our estimates imperfectly correlated, because $y_0$ and $f_{caut,0}$ have different predicted impacts on the overall average frequency of campaign settlements and proxy fights.
The main conclusion from Online Appendix 3 is that no two parameters estimates are that strongly correlated with each other. If the model were under-identified, the Hessian matrix $G$ would be either singular or close enough to singular that the inverse had extreme or imaginary covariance values. Instead, we find a well-behaved inverse, suggesting our estimator is well-identified.

Appendix E. Robustness

E.1. Exogenous parameter choices

As described in Section 4.3, we fix exogenous values for two parameters we have no hope of identifying in the data: activist’s discount factor $\delta$ and the arrival rate of campaign opportunities $\lambda_c$. For our main results, we fix $\delta = 0.9$ and $\lambda_c = 10$. We now examine how changing these values affects our main results. For each alternative parameter value, we re-estimate the main parameters $\theta$ using maximum likelihood and summarize our main results. Specifically, we estimate the fraction of 13-D and Fight choices by activists that are taken at a short-term loss to build reputation, as described in Section 5.4, and the decreases in campaign success in a no-reputation counterfactual, as described in Section 5.5.

We begin with two alternative values for $\delta$, 0.85 and 0.95. Panel A of Online Appendix Table 4 shows that changing $\delta$ has only a small impact on parameter estimates. Panel B shows that our main results only vary slightly with changes in $\delta$. Increasing $\delta$ to 0.95 makes activist more patient, resulting in a greater willingness to take costly actions as investments in reputation, which translates into larger estimates for the counterfactual drop in aggressiveness without reputation. Decreasing $\delta$ has the opposite effect. However, Panel B shows these effects are small; across all three values of $\delta$, we estimate around 20% of observed campaign initiations and proxy fights are driven by reputation-building incentives, and between 46% and 57% of the value added for target shareholders would disappear without reputation.

We also consider four alternative values for annualized $\lambda_c$, 5, 7.5, 15, and 20. We find that variations in $\lambda_c$ between 7.5 and 20 have only small impacts on our main results because
the average 13-D probabilities \((d_{h,0})\) scale up or down proportionally so that the product of \(\lambda_c\) and \(d_{h,0}\) remain near the average value for low reputation activists in our sample. This substitution and the fact that we cannot observe campaign opportunities the activist ignores are precisely why we cannot identify \(\lambda_c\).

The only alternative parameterization with substantially weaker results is if we set the arrival rate of campaign opportunities, \(\lambda_c\), to 5 per year or lower. Without frequent enough campaign opportunities, the value of building a strong reputation is diminished, which in turn diminishes reputation-seeking behavior and the overall economic importance of reputation. Such infrequent arrivals of campaign opportunities is also inconsistent with the behavior of high reputation activists in the data. For example, high reputation activists\(^5\) initiate more than 5 campaigns in 35% of years, which would be very unlikely with \(\lambda_c = 5\) even if high reputation activists always chose 13-D. As long as \(\lambda_c\) is large enough to avoid this constraint, increases in \(\lambda_c\) are observationally equivalent to decreases in the probability of choosing 13-D, and therefore have only minimal effects on our main results.

\(E.2. \quad \textit{Empirical implementation}\)

We next show our results are robust to two alternative empirical implementations. The first is using longer-term target stock returns around campaign initiation dates. Our baseline results use 3-day CARs from the \([-1,1]\) window around the 13-D announcement date. As an alternative specification, we consider 20-day CARs from the \([-10,10]\) window. The longer return window has the advantage of including any increase in prices before or after the 13-D filing attributable to price pressure by activists. However, it has the disadvantage of including much more noise from other events affecting the firm in the two month window, which increases the standard deviation of \(CAR\) from 9% to 18%. Column (8) of Online Appendix Table 4 shows that this change has a negligible impact on our parameter estimates and main results.

\(\text{---5Defined as having average reputation over 50%, the cutoff used in Table 4).}\)
The second alternative implementation we consider uses fixed values for \( \hat{a}_i \), the probability the target takes action \( i \) in the absence of activism, across all campaigns rather than campaign-specific fitted values from the cross-sectional regression described in Appendix C. While campaign-specific \( \hat{a}_i \) allows us to address the possibility high reputation activists systematically select different targets, it introduces the concern that our results are driven by choices we made it modelling \( \hat{a}_i \). To mitigate these concerns, we re-estimate the model with \( \hat{a}_i \) fixed for all campaigns to equal its mean value from our main specification. Column (9) of Online Appendix Table 4 shows this change also has almost no impact on our main results.

E.3. Modelling assumptions

Finally, estimate two variations of our model under alternative assumptions. First, we consider the possibility that the average return for target shareholders when the campaign is successful, \( \Delta \), varies randomly across campaigns instead of being fixed.\(^6\) We do so by adding random variation across campaigns in \( \tilde{\Delta} \), assuming that the realization of \( \tilde{\Delta} \) is common knowledge for both the activist and target prior to the campaign, and is independent of the other random cost realizations (e.g. \( \tilde{L} \)). Because this possibility necessitates solving the model independently for each possible realization of \( \tilde{\Delta} \), we limit the distribution to three discrete possibilities:

\[
\tilde{\Delta} = \Delta \times \begin{cases} 
0.5 & \text{w.p.} \ \frac{1}{3}, \\
1.0 & \text{w.p.} \ \frac{1}{3}, \\
1.5 & \text{w.p.} \ \frac{1}{3}, 
\end{cases}
\] (17)

This approach results in the same set of exogenous parameters to estimate as in our baseline model but with \( \Delta \) replacing the fixed \( \Delta \).

We plot the equilibrium strategies in this alternative model in Online Appendix Figure 4. As illustrated by these plots, the main effect of random variation in \( \tilde{\Delta} \) is added ‘noise’ in the

\(^6\)Online Appendix B discusses the possibility that different different activists have different \( \Delta \).
relations between \( r_t \) and observed decisions. Even high \( r_t \) activists are unlikely to file a 13-D, receive a settlement, or initiate a proxy fight when \( \Delta \) is low, while low \( r_t \) activists are quite aggressive and successful when \( \bar{\Delta} \) is high. However, average behavior across realizations of \( \Delta \) is quite similar to what we find in the baseline model, which may not be surprising given that shape offers the best fit to observed data.

Column (10) of Online Appendix Table 4 presents the parameter estimates and main results for this alternative model with variations in \( \Delta \). We estimate a larger precision (smaller standard deviation) for the cost of initiating campaign \( (\tau_L) \), indicating variations in \( \bar{\Delta} \) serve as a substitute for variations in \( (\bar{L}) \). We also find substantially-less aggressive behavior for activists with \( r_t = 0 \) and \( \bar{\Delta} = \bar{\Delta} \). The reason for that the baseline rates of campaign initiation, settlements, and proxy fights are all quite low, meaning we estimate that most of them occur in the third of campaigns with \( \bar{\Delta} = 1.5\Delta \).

Despite changes to parameter estimates when \( \bar{\Delta} \) is random, the main economic results remain largely unchanged: 18% of campaigns and 29% of proxy fights are initiated due to reputation-building motives, and the value added for target shareholders by activism would decrease by 35% without reputation when \( \Delta \) is random. The reason these main results are more stable is that, unlike the model parameters, they are driven by the shape of the relations between \( r_t \) and average observables, which remain mostly unchanged in this alternative model.

In our second alternative modelling assumption, we posit that proxy fights only succeed with probability \( \phi = 57\% \), the estimated success rate of proxy fights from Table 3 of Gantchev (2013). We assume that all proxy fights have this same success rate and that both managers and activists pay the cost of proxy fights \( (F_A \text{ and } F_M) \) regardless of whether the proxy fight’s outcome. This makes the revised stage game tree:

Stage game tree with random proxy fight outcome

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The main effect of this change is in our estimates of $\beta_i$, the added likelihood target takes observable action $i$ given a successful campaign. We identify these parameters using the additional likelihood of the action (average $a_i - \hat{a}_i$) in campaigns featuring a proxy fight. In our baseline model, we assume these campaigns are all successful and so:

$$\beta_i = \frac{1}{N_{proxy}} \sum_{c=1}^{N_{proxy}} (a_{i,c} - \hat{a}_{i,c}) ,$$

(18)

where $N_{proxy}$ is the number of campaigns with $Proxy = 1$. In the alternative model where only a fraction $\phi$ of proxy fights are successful, we define $\beta_i^\phi$ as the additional likelihood of each action when the project occurs, meaning that conditional on an observed proxy fight (but not conditioning on its outcome), the added probability of action $i$ is $\phi \beta_i^\phi$, and we have:

$$\beta_i^\phi = \frac{1}{N_{proxy}} \frac{1}{\phi} \sum_{c=1}^{N_{proxy}} (a_{i,c} - \hat{a}_{i,c}) = \frac{\beta_i}{\phi}$$

(19)

Numerically, this results in the following changes in our estimates of $\beta_i$:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Baseline</th>
<th>$\phi = 0.57$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_{reorg}$</td>
<td>Added prob. of reorganization in successful camp. (%)</td>
<td>32.3</td>
<td>56.6</td>
</tr>
<tr>
<td>$\beta_{payout}$</td>
<td>Added prob. of payout increase in successful camp. (%)</td>
<td>6.2</td>
<td>10.8</td>
</tr>
<tr>
<td>$\beta_{ceo}$</td>
<td>Added prob. of CEO change in successful camp. (%)</td>
<td>17.5</td>
<td>30.7</td>
</tr>
<tr>
<td>$\beta_{board}$</td>
<td>Added prob. of board change in successful camp. (%)</td>
<td>67.6</td>
<td>100.0</td>
</tr>
<tr>
<td>$\beta_{acq}$</td>
<td>Added prob. of M&amp;A activity in successful camp. (%)</td>
<td>30.8</td>
<td>54.0</td>
</tr>
</tbody>
</table>
Note that we truncate \( \beta_{board} \) above at 100%, meaning that in this alternative model successful campaigns always result in a change in board composition.

Holding cost parameters fixed, allowing some proxy fights to fail makes activists less likely to initiate proxy fights and managers less likely to settle. However, to fit the properties of the data, our estimation adjusts the cost distribution parameters so that proxy fights and settlements are once again as likely in the model as they are empirically. The resulting estimates, presented in Column (11) of Online Appendix Table 4, indicate only small differences in the main implications of our model: reputation-building incentives explain 12% of observed proxy fights and 19% of campaign initiations, and without reputation activists would create 39% less value for target shareholders.

Appendix F. Reputation and cumulative target returns

Tables 5 and 6 show that the empirical relation between \( r_t \) and \( CAR \) is weaker than the model-implied relation. One potential reason is that market prices do not react to the information contained in campaign initiations entirely during the \([-1,+1]\) announcement window we focus on. Instead, targets of high reputation activists could outperform targets of low reputation activists prior to the announcement window due to information leakage, or after the announcement window due to a delayed reaction.

We assess these possibilities by regressing cumulative returns starting 10 days prior to the announcement, \( CAR_{t-10,t+s} \), on \( r_t \) for values of \( s \) from \(-10\) through 252, and plot the resulting coefficients and confidence intervals in Online Appendix Figure 3. We find that only around a third of the total effect of reputation on target returns occurs during the narrow announcement window, with around 1 percentage point extra occurring beforehand and another 2.5 occurring afterwards. This pattern is consistent with some degree of information leakage and delayed market reactions.
Appendix G. Non hedge fund activists

In our final set of tests, we extend our analysis to consider the role of reputation for non hedge fund activists. As discussed in Section 4.1, our main analysis studies hedge fund activists because they are the focus of most literature on activist investors and the best-equipped to make costly investments in reputation given their institutional structure reduces concerns about outflows (see Starks (1987), Ackermann, McEnally, and Ravenscraft (1999), and Stulz (2007)). However, our model could also apply to non hedge fund activists, but perhaps with a different parameterization that reflects their differing costs and abilities.

Panel A of Online Appendix Table 5 compares summary statistics for the hedge fund and non hedge fund samples. We find that non hedge fund activists initiate fewer campaigns and have lower average AbActions, CAR, and Proxy. We further decompose non hedge fund activists into six categories: the first is Gamco, a mutual fund manager that has by far the most campaigns in our sample of any activist (345), hedge fund or otherwise. We summarize them in a separate category because they behave differently than other activists, rapidly filing 13-Ds despite almost never initiating proxy fights and generating low average AbActions. Other mutual funds only lead 38 total campaigns, but these campaigns appear to be as successful as those by hedge funds. Private equity funds, broker dealers, pension funds, and other activists categories all have lower average CAR and Proxy, and all but pension funds extract fewer AbActions in non-proxy campaigns than hedge funds.

To shed light on why non hedge fund activists behave differently, and receive different responses from their targets, we apply our reputation measure based on parameters estimated on the hedge fund sample to the non hedge fund sample. We find that our baseline reputation measure is strongly correlated with campaign frequency (13-D). However, the same measure is only weakly, or in some cases negatively, related to CAR, AbActions when Proxy = 0, and Proxy. These results indicate that the non hedge fund activists our baseline reputation measure identifies as aggressive types initiate more campaigns but not more proxy fights,
and are therefore no more successful on a per-campaign basis.

Given the apparent differences in equilibrium behavior for non hedge fund activists illustrated in Panel A of Online Appendix Table 5, it is possible a different set of model parameters explains the non hedge fund sample better than applying our baseline reputation measure. We evaluate this possibility by re-estimating our model in the non hedge fund sample, and find the substantially different set of parameters presented in Panel B of Online Appendix Table 5. Non hedge fund activists propose less-valueable projects (lower $\Delta$) and fight less frequently (lower $f_{caut,0}$ and $f_{agr,0}$). On the other hand, they initiate more campaigns (higher $d_{caut,0}$), and are more sensitive to changes in settle probability when making campaign initiation decisions (higher $\tau_L$).

The biggest difference between hedge fund activists and other activists and is in the behavior of aggressive types. Aggressive type hedge funds choose Fight with much higher probability than cautious hedge funds, resulting in a strong relation between reputation and campaign success in addition to campaign frequency. Aggressive type non hedge funds choose Fight only slightly more often than their cautious counterparts, weakening the relation between reputation and campaign success. At the same time, due the higher $\tau_L$, aggressive non hedge funds initiate campaigns much more frequently. In short, high reputation hedge fund activists fight more, which translates to future success, while high reputation non hedge fund activists merely campaign more, which does not.

Appendix H. Computing our reputation measure

In this Appendix, we provide detailed instructions on how to compute our reputation measure in future research. As an alternative, we have also posted a dataset containing our reputation measure and main outcome variables on one of the authors’ websites.

Computing our reputation measure $r_t$ entails the following steps:

1. Assemble a panel dataset of activist campaigns with the following variables (as defined in Appendix B of the paper): the date of the 13-D filing, an activist identifier, $CAR$, 

2. Choose model parameters either by re-estimating the model as described in Section 4.3 or using the parameters we estimate and present in Table 2.

3. Numerically compute the equilibrium using value function iteration on a discrete grid, as outlined in Appendix A.

4. Compute the reputation updating functions that specify post-campaign reputation \( r_{t+} \) as a function of pre-campaign reputation and the observables \( Proxy \) and \( a \). We detail this process in Appendix A, and plot the results in Figure 1 of the paper.

5. Iterate through each activists’ campaigns computing pre- and post-campaign reputations. Prior to the first campaign for each activist \( r_t \) equals \( r_0 \), which is defined so that the activist’s reputation conditional on initiated a campaign equals the unconditional reputation \( r_0 \):

\[
\mathbb{P}(\mu_A = \mu_{agr} | r_0, 13-D) = r_0. \tag{20}
\]

Using equilibrium strategies when \( r_t = r_0 \) and observed \( Proxy \) and \( a \) for the first campaign, compute the post-campaign reputation, then compute the pre-campaign reputation for the second campaign based on the number of days using Equation (25), and continue iterating until the activists’ last campaign.
References


Online Appendix Figure 1: All Comparative Statics

We show how different parameterizations of our model affect equilibrium strategies as a function of activist reputation $r_t$. The strategies are expressed by $d_{caut}$ and $d_{agr}$, the probabilities cautious and aggressive activists choose 13-D, respectively, presented in Panel A; $y$, the probability the target chooses Settle, presented in Panel B; and $f_{caut}$ and $f_{agr}$, the probabilities cautious and aggressive A choose Fight, respectively, presented in Panel C. The solid lines represents the baseline strategy in our model with estimated parameters presented in Table 2, while the dotted lines represent the equilibrium strategies when a single parameter is increased by 50%. Grey lines represent cautious A’s strategies.

Panel A: Equilibrium probabilities A chooses 13-D

[Graphs showing the changes in $d_{agr}$ and $d_{caut}$ as $\Delta$, $d_{caut,0}$, $\tau_L$, $y_0$, $\lambda_{caut}$, and $\lambda_r$ increase.]
Online Appendix Figure 1: [Continued] All Comparative Statics

Panel B: Equilibrium probabilities $M$ chooses Settle

- $y$ as $\Delta \uparrow$
- $y$ as $d_{\text{cont},0} \uparrow$
- $y$ as $\tau_L \uparrow$
- $y$ as $y_0 \uparrow$

- $y$ as $\tau_M \uparrow$
- $y$ as $f_{\text{cont},0} \uparrow$
- $y$ as $f_{\text{agr},0} \uparrow$

- $y$ as $\tau_A \uparrow$
- $y$ as $r_0 \uparrow$
- $y$ as $\lambda_\tau \uparrow$
Panel C: Equilibrium probabilities $A$ chooses Fight

- $f_{agr}$ and $f_{caut}$ as $\Delta \uparrow$
  - $\Delta=9.9\%$
  - $\Delta=6.6\%$

- $f_{agr}$ and $f_{caut}$ as $d_{caut,0} \uparrow$
  - $d_{caut,0}=6.2\%$
  - $d_{caut,0}=4.2\%$

- $f_{agr}$ and $f_{caut}$ as $\tau_{L} \uparrow$
  - $\tau_{L}=2.48$
  - $\tau_{L}=1.65$

- $f_{agr}$ and $f_{caut}$ as $y_{\theta} \uparrow$
  - $y_{\theta}=21.8\%$
  - $y_{\theta}=32.7\%$

- $f_{agr}$ and $f_{caut}$ as $\tau_{M} \uparrow$
  - $\tau_{M}=0.49$
  - $\tau_{M}=0.33$

- $f_{agr}$ and $f_{caut}$ as $f_{agr,0} \uparrow$
  - $f_{agr,0}=16.6\%$
  - $f_{agr,0}=11.1\%$

- $f_{agr}$ and $f_{caut}$ as $r_{\theta} \uparrow$
  - $r_{\theta}=3.1\%$
  - $r_{\theta}=2.1\%$

- $f_{agr}$ and $f_{caut}$ as $\lambda_{r} \uparrow$
  - $\lambda_{r}=0.19$
  - $\lambda_{r}=0.28$
We show how different parameterizations affect model-predicted observable outcomes as a function of activist reputation $r_t$. The outcomes are $13-D/yr$, the annualized rate at which an activist initiates a campaigns, presented in Panel A; $P(\text{Settle})$, the percent probability a campaign is settled, presented in Panel B; $P(\text{Fight})$, the percent probability a campaign ends in a proxy fight, presented in Panel C; $(r_{t+} - r_t)|\text{Settle}$, the increase in $r_t$ after a campaign ending in Settle, presented in Panel D; $(r_{t+} - r_t)|\text{Fight}$, the increase in $r_t$ after a campaign ending in Fight, presented in Panel E; $r_t(s)$, the value of $r_t$ after $s$ days without a campaign initiation given $r_t(0) = 99\%$, presented in Panel F; and Expected CAR, the expected campaign announcement return for the target stock, presented in Panel G. The solid line in each plot represents the baseline functional form in our model with estimated parameters presented in Table 2, while the dotted line presents the equilibrium functional form when a single parameter is increased by 50%.

Panel A: Predicted campaigns per year
Online Appendix Figure 2: [Continued] All Identification Plots

Panel B: Predicted likelihood outcome is Settle (%)
Online Appendix Figure 2: [Continued] All Identification Plots

Panel C: Equilibrium probability outcome is Fight
Panel D: Reputation increase following campaign ending in settlement

\[ (r_{t+} - r_{t}) \mid \text{Settle as } \Delta \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } d_{\text{cont},0} \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } \tau_{L} \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } y_{0} \uparrow \]

\[ (r_{t+} - r_{t}) \mid \text{Settle as } \tau_{M} \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } f_{\text{cont},0} \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } f_{\text{agr},0} \uparrow \]

\[ (r_{t+} - r_{t}) \mid \text{Settle as } \tau_{A} \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } r_{0} \uparrow \]
\[ (r_{t+} - r_{t}) \mid \text{Settle as } \lambda_{r} \uparrow \]
Online Appendix Figure 2: [Continued] All Identification Plots

Panel E: Reputation increase following campaign ending in proxy fight

\[ (r_{t+} - r_t) | \text{Fight as } \Delta \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } d_{\text{cont},0} \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } \tau_L \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } y_0 \uparrow \]

\[ (r_{t+} - r_t) | \text{Fight as } \tau_M \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } f_{\text{cont},0} \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } f_{\text{agr},0} \uparrow \]

\[ (r_{t+} - r_t) | \text{Fight as } \tau_A \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } r_0 \uparrow \]
\[ (r_{t+} - r_t) | \text{Fight as } \lambda_r \uparrow \]
Online Appendix Figure 2: [Continued] All Identification Plots

Panel F: Reputation decay between campaigns

$r_l(s)$ as $\Delta \uparrow$

- $\Delta = 9.9\%$
- $\Delta = 6.6\%$

$r_l(s)$ as $d_{\text{cand},0} \uparrow$

- $d_{\text{cand},0} = 4.2\%$
- $d_{\text{cand},0} = 6.2\%$

$r_l(s)$ as $\tau_L \uparrow$

- $\tau_L = 1.65$
- $\tau_L = 2.48$

$r_l(s)$ as $y_0 \uparrow$

- $y_0 = 32.7\%$
- $y_0 = 21.8\%$

$r_l(s)$ as $\tau_M \uparrow$

- $\tau_M = 0.49$
- $\tau_M = 0.33$

$r_l(s)$ as $f_{\text{cand},0} \uparrow$

- $f_{\text{cand},0} = 16.6\%$
- $f_{\text{cand},0} = 11.1\%$

$r_l(s)$ as $f_{\text{agr},0} \uparrow$

- $f_{\text{agr},0} = 48.6\%$
- $f_{\text{agr},0} = 72.0\%$

$r_l(s)$ as $\tau_A \uparrow$

- $\tau_A = 2.18$
- $\tau_A = 1.45$

$r_l(s)$ as $r_0 \uparrow$

- $r_0 = 3.1\%$
- $r_0 = 2.1\%$

$r_l(s)$ as $\lambda_r \uparrow$

- $\lambda_r = 0.19$
- $\lambda_r = 0.28$

$s = \text{days since prev. camp.}$
Online Appendix Figure 2: [Continued] All Identification Plots

Panel G: Expected CAR

- **E(CAR) as $\Delta \uparrow$**
  - $\Delta = 9.9\%$
  - $\Delta = 6.6\%$

- **E(CAR) as $d_{cunt,0} \uparrow$**
  - $d_{cunt,0} = 6.2\%$
  - $d_{cunt,0} = 4.2\%$

- **E(CAR) as $\tau_L \uparrow$**
  - $\tau_L = 2.48$
  - $\tau_L = 1.65$

- **E(CAR) as $y_0 \uparrow$**
  - $y_0 = 32.7\%$
  - $y_0 = 21.8\%$

- **E(CAR) as $\tau_M \uparrow$**
  - $\tau_M = 0.49$
  - $\tau_M = 0.33$

- **E(CAR) as $f_{cunt,0} \uparrow$**
  - $f_{cunt,0} = 16.6\%$
  - $f_{cunt,0} = 11.1\%$

- **E(CAR) as $f_{agr,0} \uparrow$**
  - $f_{agr,0} = 72.0\%$
  - $f_{agr,0} = 48.0\%$

- **E(CAR) as $\tau_A \uparrow$**
  - $\tau_A = 2.18$
  - $\tau_A = 1.45$

- **E(CAR) as $r_0 \uparrow$**
  - $r_0 = 3.1\%$
  - $r_0 = 2.1\%$

- **E(CAR) as $\lambda_r \uparrow$**
  - $\lambda_r = 0.19$
  - $\lambda_r = 0.28$
Online Appendix Figure 3: Reputation and Cumulative Target Returns

We plot coefficients from regressions of $CAR_{t-10,t+s}$ on $r_t$ for values of $s$ ranging from $-10$ through $252$, where $CAR_{t-10,t+s}$ is the target firm’s cumulative market adjusted return from 10 trading days before the campaign announcement through $s$ days relative to the announcement, and $r_t$ is the activist’s pre-campaign reputation. The grey area represents the 90% confidence interval for each coefficient based on standard errors clustered by activist. Our sample consists of 2,434 campaigns initiated by hedge funds during 1999–2016.
Online Appendix Figure 4: Estimated Equilibrium with Random $\Delta$

We plot equilibrium properties of our alternative model wherein the value of the project $\Delta$ randomly takes one of three values, using the estimated parameters presented in Online Appendix Table 4. The first plot shows the probability each type of activist chooses $13-D$. The second shows the probability the target chooses $\text{Settle}$. The third shows the probability each type of activist chooses $\text{Fight}$. All three plots are a function of pre-campaign reputation $r_t$. The subscript $agr$ represents the aggressive type activist, while $caut$ represents the cautious type activist. Hi $\Delta$, Med $\Delta$, and Lo $\Delta$ represent the three possible values of $\Delta$, 6.9%, 4.6%, and 2.3%, respectively.
Online Appendix Table 1: Construction of Campaign Outcome Propensity Variables

This table shows the average coefficients from each of our 56 quarterly cross-sectional predictive regressions which we use to construct predicted values for activism-related corporate actions by targets. These regressions predict values for five indicator variables: \( \text{Reorg}_{j,t+4} \), for whether firm \( j \) initiates a restructuring; \( \text{Payout}_{j,t+4} \), for whether firm \( j \) increases payouts substantially; \( \text{CEO}_{j,t+4} \), for whether firm \( j \) changes CEO; \( \text{Board}_{j,t+4} \), for whether firm \( j \) changes board composition due to activism; and \( \text{Acq}_{j,t+4} \), for whether firm \( j \) engages in a merger or acquisition, all measured in the year following campaign initiation in quarter \( t \) and multiplied by 100. \( \text{Actions}_{j,t+4} \) is the sum of the five indicator variables. Independent variables are firm characteristics we describe in Appendix B of the paper. We present \( t \)-statistics calculated in a manner similar to Fama-McBeth cross-sectional regressions in parenthesis. *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

<table>
<thead>
<tr>
<th>( \text{Log Size}_{j,t} )</th>
<th>( \text{Reorg}_{j,t+4} )</th>
<th>( \text{Payout}_{j,t+4} )</th>
<th>( \text{CEO}_{j,t+4} )</th>
<th>( \text{Board}_{j,t+4} )</th>
<th>( \text{Acq}_{j,t+4} )</th>
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<td>( (1) )</td>
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<td>( (4) )</td>
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<tr>
<td>3.62***</td>
<td>2.13***</td>
<td>0.24***</td>
<td>-0.14</td>
<td>-0.10***</td>
<td>1.50***</td>
</tr>
<tr>
<td>(13.27)</td>
<td>(16.53)</td>
<td>(2.91)</td>
<td>(1.53)</td>
<td>(6.66)</td>
<td>(10.00)</td>
</tr>
<tr>
<td>( EBIT/\text{Assets}_{j,t} )</td>
<td>1.51*</td>
<td>0.95***</td>
<td>4.12***</td>
<td>-2.28***</td>
<td>-0.1**</td>
</tr>
<tr>
<td>( (1.82) )</td>
<td>( (2.71) )</td>
<td>( (15.19) )</td>
<td>( (6.66) )</td>
<td>( (2.23) )</td>
<td>( (3.52) )</td>
</tr>
<tr>
<td>( \text{Net Leverage}_{j,t} )</td>
<td>-4.05***</td>
<td>0.4*</td>
<td>-5.33***</td>
<td>-0.95***</td>
<td>-0.01</td>
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<tr>
<td>( (7.57) )</td>
<td>( (1.76) )</td>
<td>( (18.85) )</td>
<td>( (5.65) )</td>
<td>( (0.27) )</td>
<td>( (10.31) )</td>
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<tr>
<td>( \text{Payout/\text{Assets}_{j,t}} )</td>
<td>198.01***</td>
<td>-7.67***</td>
<td>216.54***</td>
<td>-0.02</td>
<td>-0.34**</td>
</tr>
<tr>
<td>( (32.71) )</td>
<td>( (3.97) )</td>
<td>( (46.93) )</td>
<td>( (0.02) )</td>
<td>( (2.28) )</td>
<td>( (11.04) )</td>
</tr>
<tr>
<td>( \text{Capex/\text{Assets}_{j,t}} )</td>
<td>12.06***</td>
<td>2.20***</td>
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<td>0.19*</td>
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<tr>
<td>( (11.72) )</td>
<td>( (3.14) )</td>
<td>( (12.02) )</td>
<td>( (2.40) )</td>
<td>( (1.84) )</td>
<td>( (2.49) )</td>
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<td>( \text{Book to Market}_{j,t} )</td>
<td>0.16***</td>
<td>0.06***</td>
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<td>0.02***</td>
<td>-0.001***</td>
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<td>( (9.57) )</td>
<td>( (10.23) )</td>
<td>( (3.90) )</td>
<td>( (6.60) )</td>
<td>( (6.77) )</td>
<td>( (8.40) )</td>
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<td>( \text{Inst Ownership}_{j,t} )</td>
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<td>3.44***</td>
<td>0.70***</td>
<td>1.35***</td>
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<td>( (12.44) )</td>
<td>( (12.43) )</td>
<td>( (3.98) )</td>
<td>( (9.86) )</td>
<td>( (6.75) )</td>
<td>( (0.80) )</td>
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<tr>
<td>1 Year Return( j,t )</td>
<td>-7.77***</td>
<td>-4.93***</td>
<td>2.05***</td>
<td>-2.41***</td>
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<tr>
<td>( (10.55) )</td>
<td>( (11.46) )</td>
<td>( (10.93) )</td>
<td>( (11.18) )</td>
<td>( (1.64) )</td>
<td>( (9.48) )</td>
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<tr>
<td>Average R(^2)</td>
<td>0.087</td>
<td>0.070</td>
<td>0.186</td>
<td>0.008</td>
<td>0.002</td>
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Online Appendix Table 2: Aggressiveness and Idea Quality

Panel A presents panel regressions predicting the number of abnormal activist-friendly actions taken by the targets of activist campaigns (AbActions) using PastProxy, the fraction of past campaigns by the activist ending in a proxy fight; PastAbActions, the average Ab Actions during the activists’ prior campaigns; Past 13-D, the annualized fraction of past days on which the activist initiated a campaign; PastCAR250|Proxy, the average 250-day cumulative abnormal return (CAR250) for the activist’s past targets in campaigns featuring a proxy fight; PastCAR250|HiAct, the average CAR250 for the activist’s past targets in campaigns with higher than median Ab Actions; and PastCAR250, the average CAR250 in all prior campaigns by the activist. Panel B presents regressions with the same independent variables predicting CAR, the 3-day target return around the campaign announcement date. Panel C shows regressions with the same independent variables predicting future values of the same outcome, for example Past Proxy predicting Proxy in Column (1). The sample includes 2,434 campaigns initiated by hedge funds during 1999–2016. We present standard errors, which we cluster by activist, in parenthesis. *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

### Panel A: Predicting Abnormal Target Actions in Non-Proxy Campaigns (Ab Actions × 100)

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<tbody>
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<td>Past Proxy</td>
<td>11.06***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>8.94**</td>
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<td></td>
<td>(4.07)</td>
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<td>(4.05)</td>
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<tr>
<td>Past Ab Actions</td>
<td>10.57***</td>
<td>7.64*</td>
<td></td>
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<td></td>
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<tr>
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<td>(3.98)</td>
<td>(4.01)</td>
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<tr>
<td>Past 13-D</td>
<td>12.16***</td>
<td>11.08***</td>
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<td></td>
<td>(3.86)</td>
<td>(3.84)</td>
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<tr>
<td>Past CAR250</td>
<td>Proxy</td>
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<td>−5.91*</td>
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<td>(5.22)</td>
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<td>Past CAR250</td>
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### Panel B: Predicting Campaign Announcement Returns (CAR × 100)

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<td>Past Proxy</td>
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<td></td>
<td>(0.22)</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td>(0.22)</td>
</tr>
<tr>
<td>Past Ab Actions</td>
<td></td>
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<td>0.08</td>
<td></td>
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<td>(0.22)</td>
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<tr>
<td>Past 13-D</td>
<td></td>
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<td></td>
<td>0.33</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.23)</td>
<td></td>
<td>(0.24)</td>
<td></td>
<td></td>
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<tr>
<td>Past CAR250</td>
<td>Proxy</td>
<td>−0.10</td>
<td>−0.07</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
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<td></td>
<td>(0.22)</td>
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<tr>
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<td></td>
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<td>(0.32)</td>
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<td>(0.50)</td>
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</tr>
<tr>
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<td></td>
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<td>(0.29)</td>
<td>(0.44)</td>
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### Panel C: Campaign Outcome Persistences

<table>
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<th>(4)</th>
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<tr>
<td>Proxy Ab Actions</td>
<td>0.58***</td>
<td>0.39**</td>
<td>0.41***</td>
<td>0.28***</td>
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<td></td>
<td>(0.08)</td>
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<td>(0.15)</td>
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Online Appendix Table 3: Correlation of Parameter Estimates

This table shows the correlation of parameter estimates. We compute this correlation using the same procedure used to compute standard errors, as described in Online Appendix C. We omit correlations below 0.25 in absolute value for brevity, and highlight in grey the correlations we discuss in Online Appendix D.

<table>
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<th>$\Delta$</th>
<th>$d_{caut,0}$</th>
<th>$\tau_L$</th>
<th>$y_0$</th>
<th>$\tau_M$</th>
<th>$f_{caut,0}$</th>
<th>$f_{agr,0}$</th>
<th>$\tau_A$</th>
<th>$\tau_0$</th>
<th>$\lambda_r$</th>
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</thead>
<tbody>
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<td>$d_{caut,0}$</td>
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<td>-0.84</td>
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<td>0.48</td>
<td>-0.29</td>
<td>-0.64</td>
<td>-0.54</td>
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</tr>
<tr>
<td>$\tau_L$</td>
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<td>-0.60</td>
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<td></td>
<td>0.59</td>
<td>0.56</td>
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<td></td>
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<tr>
<td>$y_0$</td>
<td>1.00</td>
<td>0.26</td>
<td>0.41</td>
<td>-0.37</td>
<td>0.34</td>
<td>-0.38</td>
<td>-0.68</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\tau_M$</td>
<td>1.00</td>
<td>0.53</td>
<td></td>
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<td></td>
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<td>-0.52</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f_{caut,0}$</td>
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<td></td>
<td></td>
<td></td>
<td>-0.50</td>
<td>-0.64</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>$f_{agr,0}$</td>
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<td></td>
</tr>
<tr>
<td>$\tau_A$</td>
<td>1.00</td>
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<td>-0.33</td>
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<td></td>
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</tr>
<tr>
<td>$\tau_0$</td>
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</tr>
<tr>
<td>$\lambda_r$</td>
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<td></td>
<td></td>
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</tbody>
</table>
Online Appendix Table 4: Robustness

In Panel A we present panel regressions using our model-based reputation measure \( r_t \) to predict four dependent variables: The first is 13-D, an indicator for whether there is a campaign initiation on a given activist-day. The second is Ab Actions, the total number of abnormal activism-related corporate actions by target firms in the year following campaign initiation. The third is CAR, the target’s [-1,1] market-adjusted return around the campaign initiation date. The fourth is Proxy, an indicator for whether the campaign features a proxy fight. In Panel B we show similar regressions, but include additional activist characteristics, which we describe in Appendix B, as controls. Panel C we show similar regressions, but include Past CAR\(_{250}\)\( \mid \)Proxy, Past CAR\(_{250}\)\( \mid \)Hi Act, and Past CAR\(_{250}\) which we use to measure activist idea quality, as additional controls. All regressions include year fixed effects. Our sample for 13-D is 737,004 activist-days during 1999–2016. Our sample for the other variables is 2,434 campaigns initiated by hedge funds during 1999–2016. We present standard errors, which we cluster by activist, in parenthesis. *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

### Panel A: Parameter Estimates

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>( \delta = 0.85 )</th>
<th>( \delta = 0.95 )</th>
<th>( \lambda_c = 5 )</th>
<th>( \lambda_c = 7.5 )</th>
<th>( \lambda_c = 15 )</th>
<th>( \lambda_c = 20 )</th>
<th>( CAR_{250} )</th>
<th>Const. ( \bar{a}_t )</th>
<th>Rand. ( \Delta )</th>
<th>( \phi = 0.57 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_{caut,0} ) (%)</td>
<td>4.16</td>
<td>4.12</td>
<td>3.94</td>
<td>8.36</td>
<td>5.58</td>
<td>2.86</td>
<td>1.55</td>
<td>4.36</td>
<td>4.20</td>
<td>0.02</td>
<td>4.74</td>
</tr>
<tr>
<td>( \tau_L )</td>
<td>1.65</td>
<td>1.72</td>
<td>1.87</td>
<td>6.49</td>
<td>2.10</td>
<td>1.51</td>
<td>1.37</td>
<td>1.64</td>
<td>1.69</td>
<td>2.74</td>
<td>1.63</td>
</tr>
<tr>
<td>( y_0 ) (%)</td>
<td>21.82</td>
<td>21.92</td>
<td>22.05</td>
<td>25.46</td>
<td>22.64</td>
<td>21.26</td>
<td>20.70</td>
<td>21.87</td>
<td>21.65</td>
<td>14.96</td>
<td>22.73</td>
</tr>
<tr>
<td>( \tau_M )</td>
<td>0.33</td>
<td>0.33</td>
<td>0.34</td>
<td>0.21</td>
<td>0.34</td>
<td>0.33</td>
<td>0.32</td>
<td>0.33</td>
<td>0.34</td>
<td>0.28</td>
<td>0.37</td>
</tr>
<tr>
<td>( f_{caut,0} ) (%)</td>
<td>11.10</td>
<td>11.20</td>
<td>11.54</td>
<td>13.78</td>
<td>12.10</td>
<td>10.84</td>
<td>10.68</td>
<td>11.35</td>
<td>11.40</td>
<td>4.26</td>
<td>11.51</td>
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<tr>
<td>( f_{agr,0} ) (%)</td>
<td>48.03</td>
<td>47.51</td>
<td>46.10</td>
<td>48.91</td>
<td>46.01</td>
<td>46.47</td>
<td>44.94</td>
<td>46.94</td>
<td>46.66</td>
<td>33.02</td>
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<td>( \tau_A )</td>
<td>1.45</td>
<td>1.55</td>
<td>1.61</td>
<td>1.00</td>
<td>1.36</td>
<td>1.73</td>
<td>2.01</td>
<td>1.25</td>
<td>1.44</td>
<td>1.31</td>
<td>0.54</td>
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<tr>
<td>( r_0 ) (%)</td>
<td>2.05</td>
<td>2.03</td>
<td>2.25</td>
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<td>1.71</td>
<td>11.55</td>
<td>2.61</td>
<td>2.20</td>
<td>1.90</td>
<td>2.58</td>
<td>2.61</td>
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<tr>
<td>( \lambda_r )</td>
<td>0.19</td>
<td>0.19</td>
<td>0.19</td>
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<td>0.19</td>
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<td>0.17</td>
<td>0.15</td>
<td>0.19</td>
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### Panel B: Main Results

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<tr>
<th></th>
<th>Baseline</th>
<th>( \delta = 0.85 )</th>
<th>( \delta = 0.95 )</th>
<th>( \lambda_c = 5 )</th>
<th>( \lambda_c = 7.5 )</th>
<th>( \lambda_c = 15 )</th>
<th>( \lambda_c = 20 )</th>
<th>( CAR_{250} )</th>
<th>Const. ( \bar{a}_t )</th>
<th>Rand. ( \Delta )</th>
<th>( \phi = 0.57 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ch. in Pr(13-D) w/out rep. (%)</td>
<td>-39.56</td>
<td>-38.30</td>
<td>-47.77</td>
<td>-14.24</td>
<td>-39.70</td>
<td>-43.76</td>
<td>-50.72</td>
<td>-36.68</td>
<td>-40.23</td>
<td>-30.67</td>
<td>-32.14</td>
</tr>
<tr>
<td>Ch. in Pr(Fight) w/out rep. (%)</td>
<td>-29.65</td>
<td>-28.65</td>
<td>-32.92</td>
<td>-18.48</td>
<td>-25.11</td>
<td>-40.37</td>
<td>-33.50</td>
<td>-27.73</td>
<td>-28.45</td>
<td>-64.17</td>
<td>-24.64</td>
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</table>
Online Appendix Table 5: Non Hedge Fund Activists

This table compares a sample of 1,801 campaigns by non hedge fund activists to our main sample of 2,434 activist campaigns initiated by hedge funds during 1999–2016. Panel A presents summary statistics for the two samples, as well as sub-samples based on different categories of non hedge fund activists. The reputation-based moments in Panel A use $r_t$ computed with model parameters estimated on the hedge fund sample. Outcomes 13-D, Ab Actions, CAR, and Proxy are defined in Table 1. Panel B presents estimates of model parameters, defined in Table 2, in the two samples. Panel C compares some key moments and equilibrium properties in the two samples using $r_t$ computed with the parameters in Panel B.

Panel A: Moments using hedge fund parameter estimates

<table>
<thead>
<tr>
<th></th>
<th>Hedge Funds</th>
<th>All Non-HF</th>
<th>Gamco MFs</th>
<th>Other PE Funds</th>
<th>Broker Dealers</th>
<th>Pension Funds</th>
<th>Other</th>
</tr>
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<tbody>
<tr>
<td>Campaigns</td>
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<td>1801</td>
<td>345</td>
<td>38</td>
<td>122</td>
<td>111</td>
<td>105</td>
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<tr>
<td>Activists</td>
<td>420</td>
<td>603</td>
<td>1</td>
<td>10</td>
<td>19</td>
<td>15</td>
<td></td>
</tr>
<tr>
<td>Mean(13-D) (×365)</td>
<td>1.00</td>
<td>0.73</td>
<td>19.31</td>
<td>0.48</td>
<td>1.03</td>
<td>0.83</td>
<td>1.37</td>
</tr>
<tr>
<td>Mean(Ab Actions)</td>
<td>0.78</td>
<td>0.54</td>
<td>0.32</td>
<td>0.89</td>
<td>0.28</td>
<td>0.21</td>
<td>0.68</td>
</tr>
<tr>
<td>Mean(CAR) (%)</td>
<td>2.82</td>
<td>1.66</td>
<td>1.56</td>
<td>2.96</td>
<td>2.03</td>
<td>1.23</td>
<td>0.58</td>
</tr>
<tr>
<td>Mean(Proxy) (%)</td>
<td>14.30</td>
<td>6.39</td>
<td>2.32</td>
<td>5.26</td>
<td>0.82</td>
<td>0.90</td>
<td>5.71</td>
</tr>
<tr>
<td>corr($r_t$, 13-D) (%)</td>
<td>3.28</td>
<td>8.92</td>
<td>-0.28</td>
<td>3.31</td>
<td>2.07</td>
<td>1.79</td>
<td>4.71</td>
</tr>
<tr>
<td>corr($r_t$, Ab Actions) (%)</td>
<td>13.62</td>
<td>-5.84</td>
<td>-0.10</td>
<td>11.16</td>
<td>2.24</td>
<td>-11.59</td>
<td>7.74</td>
</tr>
<tr>
<td>corr($r_t$, CAR) (%)</td>
<td>6.65</td>
<td>-0.10</td>
<td>5.86</td>
<td>1.04</td>
<td>2.55</td>
<td>5.40</td>
<td>-2.56</td>
</tr>
<tr>
<td>corr($r_t$, Proxy) (%)</td>
<td>22.52</td>
<td>-5.66</td>
<td>9.16</td>
<td>-8.82</td>
<td>-1.32</td>
<td>-5.56</td>
<td>-5.51</td>
</tr>
<tr>
<td>Mean $r_t$ (%)</td>
<td>10.81</td>
<td>6.60</td>
<td>28.26</td>
<td>1.41</td>
<td>0.84</td>
<td>0.54</td>
<td>8.81</td>
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<td>Median $r_t$ (%)</td>
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<td>1.39</td>
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<td>90th perc $r_t$ (%)</td>
<td>41.87</td>
<td>22.32</td>
<td>63.01</td>
<td>3.83</td>
<td>1.84</td>
<td>1.33</td>
<td>27.86</td>
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</table>

Panel B: Non hedge fund parameter estimates

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<th></th>
<th>$\Delta$</th>
<th>$d_{h,0}$</th>
<th>$\tau_L$</th>
<th>$y_0$</th>
<th>$\tau_M$</th>
<th>$f_{caut,0}$</th>
<th>$f_{agt,0}$</th>
<th>$\tau_A$</th>
<th>$\tau_0$</th>
<th>$\lambda_r$</th>
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<tbody>
<tr>
<td>Hedge Funds</td>
<td>6.62</td>
<td>4.16</td>
<td>1.65</td>
<td>21.82</td>
<td>0.33</td>
<td>11.10</td>
<td>48.03</td>
<td>1.45</td>
<td>2.05</td>
<td>0.19</td>
</tr>
<tr>
<td>All Non HF</td>
<td>5.73</td>
<td>3.61</td>
<td>5.22</td>
<td>22.86</td>
<td>1.26</td>
<td>9.13</td>
<td>19.81</td>
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<td>0.18</td>
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Panel C. Comparing moments and equilibrium properties

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<th>All Non HF</th>
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<tbody>
<tr>
<td>corr($r_t$, 13-D) (%)</td>
<td>3.28</td>
<td>9.55</td>
</tr>
<tr>
<td>corr($r_t$, Ab Actions) (%)</td>
<td>13.62</td>
<td>-8.74</td>
</tr>
<tr>
<td>corr($r_t$, CAR) (%)</td>
<td>6.65</td>
<td>0.07</td>
</tr>
<tr>
<td>corr($r_t$, Proxy) (%)</td>
<td>22.52</td>
<td>-8.04</td>
</tr>
<tr>
<td>13-D (%) of opp.</td>
<td>9.34</td>
<td>4.44</td>
</tr>
<tr>
<td>Settle (%) of camp.</td>
<td>27.44</td>
<td>23.38</td>
</tr>
<tr>
<td>Fight (%) of refusals</td>
<td>16.85</td>
<td>9.15</td>
</tr>
<tr>
<td>Shareholder payoff/opp (bp)</td>
<td>24.53</td>
<td>7.75</td>
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</tbody>
</table>