Reputation and Investor Activism: A Structural Approach

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Abstract

We measure the impact of reputation for proxy fighting on investor activism by estimating a dynamic model in which activists engage a sequence of target firms. Our estimation produces an evolving reputation measure for each activist and quantifies its impact on campaign frequency and outcomes. We find that high reputation activists initiate 3.5 times as many campaigns and extract 85% more settlements from targets, and that reputation-building incentives explain 20% of campaign initiations and 19% of proxy fights. Our estimates indicate these reputation effects combine to nearly double the value activism adds for target shareholders.

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1. Introduction

Activists only capture a small fraction of the value they create in target firms while paying substantial private costs associated with rapidly acquiring shares, proposing and campaigning for desired changes in firm policy, and potentially organizing a proxy fight (Gantchev (2013)). In a static setting, this free-rider problem suggests activist campaigns should be rare and unsuccessful. However, empirical evidence shows campaigns are common and successful, with activists prevailing primarily by extracting settlements from target managers without a proxy fight (Brav et al. (2008), Brav, Jiang, and Kim (2010), and Bebchuk et al. (2017)). These patterns raise two related questions: why do targets settle so frequently with activists who face the large private costs of proxy fights, and why do activists initiate so many campaigns and proxy fights despite the free-rider problem?

In this paper we show activist reputation for proxy fighting ties together and explains both target settlement and costly activist aggression in a dynamic setting. We do so by estimating a dynamic model in which target managers settle more frequently with high reputation activists rather than risk a proxy fight that has negative career consequences (Fos and Tsoutsoura (2014)). These settlements provide incentives for activists to invest in reputation by incurring the costs of initiating campaigns and proxy fights. Using our estimated model, we document these reputation effects empirically and show that they combine to make activism substantially more frequent and successful than it would otherwise be.

Measuring reputation’s impact on the success of activism presents four main challenges. The first is dynamically quantifying reputation in a way that appropriately reflects all information in each activist’s track record, including the frequency and outcomes of past campaigns. The second challenge is specifying the form of reputation’s impact on observed campaign outcomes, which emerge from a non-linear equilibrium. The third challenge is assessing how much of activists’ observed behavior is driven by static cost concerns versus dynamic reputation-building, which requires estimates of activists’ unobserved costs. The
final challenge is measuring how successful activism would be in a counterfactual world without reputation, which requires estimates of no-reputation equilibrium behavior.

We address these challenges by solving and estimating a dynamic economic model that produces an evolving reputation measure for each activist in our sample, predicts how this measure relates to the frequency and outcomes of activist campaigns, allows us to estimate the extent of reputation-building behavior, and generates a no-reputation counterfactual. Our structural approach also ensures consistency between each facet of our analysis by using a single parsimonious set of parameters to construct our reputation measure and specify how it affects equilibrium behavior and outcomes.

Each activist in our model engages a series of potential target firms in a game having up to three stages. First, the activist decides whether to initiate a campaign, which entails a private cost encompassing the price impact associated with building a position in the target, the effort and expense related to communications with target managers and regulators, and any other expenses prior to a proxy fight (see Gantchev (2013)). If the activist initiates a campaign, target managers then decide whether to settle by undertaking a project that has positive net present value (NPV) for shareholders but negative net value for them due to their private costs. If target managers settle, the campaign ends and they pay the net private cost of the project, while the activist benefits from the project increasing the target’s share price. If target managers refuse to settle, the activist then decides whether to initiate a proxy fight. If they do, the project occurs and both parties receive the same payoff they get from a settlement but with an additional proxy fight cost. If the activist does not initiate a proxy fight, the engagement ends with no effect on target managers and the activist receiving no benefits to offset the campaign initiation cost.

Reputation arises in our model because targets do not know the activist’s average cost of proxy fighting (their “type”) and instead estimate it from their behavior in past campaigns. There are two types of activists in our model, “aggressive” types with higher average costs of proxy fights and “cautious” types with lower average costs. These costs encompass the
financial and non-financial costs of fighting, net of any non-financial benefits such as enjoying conflict and attention.\textsuperscript{1} Consistent with the importance of non-financial benefits to aggressive types, activists often make statements advertising their low subjective cost of proxy fights:

“I enjoy the hunt much more than the ‘good life’ after the victory.” – \textit{Carl Icahn}

A key variable affecting each stage of the activism game is the activist’s “reputation,” defined as the probability the activist is the aggressive type conditional on previous campaigns (as in Kreps and Wilson (1982) and Milgrom and Roberts (1982)). Higher reputation activists initiate more campaigns in the first stage because targets, fearing a costly proxy fight, settle more frequently with higher reputation activists in the second stage. Because activists anticipate these additional settlements in future stage games, they value higher reputations. Activists therefore have an added incentive to initiate campaigns and proxy fights, even when they are not profitable in a single campaign, as an investment in reputation.

We estimate our model using maximum likelihood by choosing the parameters that result in an equilibrium that best explains the observed data from a panel of 2,434 activist campaigns by hedge funds between 1999 and 2016. Our model yields predictions for the likelihood of campaign initiations, target stock reactions to campaign announcements, and proxy fights, all of which we observe directly using SEC filings, SharkWatch, and CRSP. Our model also yields predictions for the likelihood of settlements, which we infer from target firm actions such as board changes and mergers observed in Compustat and Capital IQ.\textsuperscript{2}

Using our estimated model parameters, we quantify reputation’s role in each stage of our activism game. In the first stage, we find high reputation activists initiate 3.5 campaigns per year, compared to only 0.6 for low reputation activists.\textsuperscript{3} Moreover, 20% of campaigns

\textsuperscript{1}Like Kreps and Wilson (1982) and Milgrom and Roberts (1982), we model different types as having different payoffs, rather than modelling one as a “commitment” type that always uses a specific mixed strategy for reasons outside the model, as in Fudenberg and Levine (1992) or Schmidt (1993).

\textsuperscript{2}Unfortunately, SharkWatch and other providers of activism data have no comprehensive classification for whether a campaign was settled, forcing empirical research on settlements (e.g. in Bebchuk et al. (2017)) to estimate whether a specific campaign was settled by combining indicators from multiple sources.

\textsuperscript{3}For these statistics, a ‘low’ reputation activist has probability less than 0.5% of being the aggressive type, while a ‘high’ reputation activist has probability above 50%.
are initiated despite not being profitable in isolation due to the benefits of reputation. In the second stage, targets settle with high reputation activists 44% of the time, compared to 29% for low reputation activists. In the third stage, high reputation activists fight 26% of the time when refused, compared to 14% for low reputation activists, and 19% of fights are initiated despite not being profitable in isolation due to the benefits of reputation.

We formally test and reject a “no reputation” version of our model in which targets do not consider the activist’s history. With this constraint, all campaigns feature the same equilibrium strategies, and independent and identically distributed (iid) outcomes. We find this alternative model fits the data significantly worse than our baseline model because campaign frequency and outcomes are highly correlated with our reputation estimates and therefore are not iid. A potential alternative explanation for the non-iid campaign outcomes is that targets directly observe the activist’s type, making campaign outcomes depend on static type but not dynamic reputation. We also test and reject this “full information” version of our model because within-activist changes in reputation also predict changes in the frequency and outcomes of their campaigns.

Having established the importance of reputation in explaining observed equilibrium behavior, we next consider how equilibrium behavior would change in a counterfactual world without reputation. We do so by retaining our baseline parameter estimates but generating a new equilibrium in which targets do not condition on the activist’s past behavior. We find that activism produces many fewer successful campaigns in this “no reputation” counterfactual for three related reasons. First, because activists have no reputation-building incentives, they initiate fewer campaigns in the counterfactual (6% of opportunities) than in our baseline model (9%). Similarly, without reputation-building incentives, activists fight less frequently (12% of the campaigns in which the target does not settle) than in our baseline model (17%). Anticipating the lower risk of a proxy fight, targets settle less frequently (24% of campaigns) than in our baseline model (27%). Combining these effects, we estimate target shareholders’ average payoff would be 48% lower without reputation.
We further illustrate the magnitude of our empirical findings and the quality of our model’s fit using linear regressions of campaign outcomes on our model-based reputation measure. We find reputation significantly predicts the frequency of campaigns, activist-friendly actions by target firms, instances of proxy fights, and abnormal target stock returns around campaign announcements. The magnitudes of these empirical relations are very close to the magnitudes predicted by our estimated model for campaign frequency and target actions, suggesting our estimated model fits well along those dimensions. The model fits less well in predicting the frequency of proxy fights, which is more sensitive to reputation in the data than in our estimated model. We also find that three-day target returns around campaign announcements are somewhat less sensitive to reputation than our model predicts, but that this relation strengthens when using larger return windows.

Our reduced-form tests allow us to assess how our model-based reputation measure relates to campaign frequency and outcomes while controlling for variables outside of our model. We find that our reputation measure is incremental to other time-varying activist characteristics, including proxies for experience and reputation adapted from Boyson, Ma, and Mooradian (2016) and Krishnan, Partnoy, and Thomas (2016), respectively.

Our final analysis compares the effects of reputation in campaigns by hedge fund activists, the focus of our main tests, to 1,801 campaigns by other activists. On average, other activists initiate fewer campaigns and fewer proxy fights, and are less successful than hedge fund activists. Re-estimating our model using only non hedge fund activists offers a potential explanation for these differences. Specifically, while aggressive-type hedge funds initiate many more campaigns and proxy fights, we find that aggressive-type non hedge funds initiate many more campaigns but only marginally more proxy fights. As a result, non hedge fund reputation predicts campaign frequency but has little bearing on campaign success.
2. Related Literature

We add a unique perspective to the theoretical literature on investor activism, which focuses on a large shareholder of a single firm (examples include Burkart, Gromb, and Panunzi (1997), Maug (1998), Aghion, Bolton, and Tirole (2004), Admati and Pfleiderer (2009), and Back et al. (2018)). In these papers, large shareholders are effective activists because their position sizes reduce the free-rider problem. More-recent work argues large blockholders may be limited in important ways (Edmans and Manso (2011) and Dasgupta and Piacentino (2015)). Levit (2019) extends this literature by examining communication and exit as alternate channels to avoid costly proxy fights, while Corum and Levit (2019) studies the role of activists in facilitating takeovers, and Corum (2018) models demands and settlements in a setting with asymmetric information about the value of the project.

Our analysis supports and extends an ongoing empirical literature on investor activism, as surveyed in Brav, Jiang, and Kim (2010) and Denes, Karpoff, and McWilliams (2017). More-recent work shows activism is effective internationally (Becht et al. (2017)); is facilitated by liquidity (Norli, Ostergaard, and Schindele (2014)) and passive investors (Appel, Gormley, and Keim (2019)); improves targets’ productive efficiency (Brav, Jiang, and Kim (2015)), governance (Gantchev, Gredil, and Jotikasthira (2019)), and innovation (Brav et al. (2018)); and increases the likelihood of mergers (Boyson, Gantchev, and Shivdasani (2017)).

Two related papers, Krishnan, Partnoy, and Thomas (2016) and Boyson, Ma, and Mooradian (2016), examine activist hedge fund reputation and experience empirically. Krishnan, Partnoy, and Thomas (2016) finds that short-term stock returns and long-term firm performance are both stronger following interventions by top hedge funds, defined as those with the highest dollar value of recent activist positions. Boyson, Ma, and Mooradian (2016) shows activists with more experience produce larger announcement returns in the future as well as better long-term firm performance. Our paper differs by using a model-based structural approach to study the impact of reputation for proxy fighting.
Bebchuk et al. (2017) finds that settlements often consist of board seats rather than corporate policy changes due to incomplete contracting, and that settlements are related to activists’ ability to credibly threaten a proxy fight. We formally model this credibility as arising in a dynamic reputation model, and assess its impact using a structural estimation.

The closest activism paper in methodology is Gantchev (2013), which estimates the net cost to activists in four stages of a campaign. Because the goal of the Gantchev (2013) model is to estimate these costs, while the goal of our model is to assess the role of reputation in the dynamic interaction between activists and their targets, the two models are quite different. Gantchev (2013) estimates a statistical sequential decision model featuring a single campaign. In contrast, we estimate an economic model with a strategic equilibrium featuring multiple campaigns, which allows us to model and quantify reputation dynamics.

Our empirical methodology is also similar to other structural estimation papers in corporate finance. As discussed in Strebulaev and Whited (2012), these papers use a variety of estimation procedures. Simulated method of moments (SMM) is employed by many recent papers, including Nikolov and Whited (2014), Dimopoulos and Sacchetto (2014), Schroth, Suarez, and Taylor (2014), Glover (2016), and Gao, Whited, and Zhang (2018). As discussed in Section 4, we use a maximum likelihood estimation, which is similar to the simulated maximum likelihood approach in Morellec, Nikolov, and Schürhoff (2012). Other papers using alternative structural estimation methodologies in corporate finance include Sørensen (2007), Korteweg (2010), Albuquerque and Schroth (2010), Matvos and Seru (2014), Kang, Lowery, and Wardlaw (2014), and Warusawitharana (2015).

3. Model

Our model adapts the canonical reputation framework with one long-lived player of unknown type and many short-lived players to investor activism. This framework originated in Kreps and Wilson (1982) and Milgrom and Roberts (1982), which study the chain-store stage game, and was generalized to other stage games in Fudenberg and Levine (1989) and Fudenberg
and Levine (1992). This reputation concept has been applied to many settings in finance (e.g. debt issuance in Diamond (1989) and investment banking in Chemmanur and Fulghieri (1994)), but to our knowledge we are the first to apply it to investor activism.

3.1. Stage Game

The core of our model is an activist campaign opportunity in which an activist $A$ and a manager $M$, each risk neutral, engage in the stage game summarized by Model Figure 1.

**Model Figure 1: Stage game tree**

\[
\begin{aligned}
&\text{Ignore} \quad [0, 0] \\
&\text{A} \quad \text{13-D} \quad \text{Settle} \quad [\Delta - \tilde{L}, \Delta - B] \\
&\quad \text{M} \quad \text{Refuse} \quad \text{Fold} \quad [-\tilde{L}, 0] \\
&\quad \text{A} \quad \text{Fight} \quad [\Delta - \tilde{L} - \tilde{F}_A, \Delta - B - \tilde{F}_M]
\end{aligned}
\]

$M$ controls a firm whose shares outstanding are normalized to one. They have access to a project with NPV $\Delta > 0$ that they do not take without intervention by $A$ because it entails private cost $B > \Delta$. Because shares outstanding are normalized to one, payoffs to $M$ and are in units of the firm’s market capitalization.

In each stage game, $A$ moves first and decides whether to initiate a campaign by purchasing shares in the target firm and filing a 13-D (13-D), or ignore the opportunity (Ignore). If $A$ chooses Ignore, the game ends and each party gets a payoff of 0. If $A$ chooses 13-D, they incur the costs $\tilde{L} > 0$ associated with an activist campaign (excluding the costs of a proxy fight). Campaign costs include the round-trip liquidity costs of buying and selling shares, as well as the effort and expense related to regulatory document submissions, communications with target managers, and fundamental research analysis (see Brav et al. (2008), Gantchev (2013), and Back et al. (2018)). Payoffs to $A$ are in units of their initial investment, so an increase in firm value by $\Delta$ also generates a payoff of $\Delta$ for $A$.  

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Filing a 13-D represents a threat to force \( M \) to enact the project via a proxy fight. However, prior to a proxy fight, \( M \) decides whether to refuse \( A \)'s demands (Refuse) or settle (Settle), in which case they undertake the project and the game ends, making the payoffs:

\[
[\Pi_{A,\text{Settle}}, \Pi_{M,\text{Settle}}] = \left[ \Delta - \tilde{L}, \Delta - B \right].
\]  

(1)

We assume \( M \) internalizes the full benefit of the project \( \Delta \), perhaps due to performance-based bonuses, making their net payoff when the project occurs \( \Delta - B \).\(^4\)

If \( M \) refuses, \( A \) decides whether or not to initiate a proxy fight (Fight or Fold). We assume proxy fights are always successful and therefore result in firm value increasing by \( \Delta \).\(^5\) However, proxy fights also have private costs for both \( A \) (\( \tilde{F}_A > 0 \)) and \( M \) (\( \tilde{F}_M > 0 \)). These costs include legal, accounting, and administrative expenses for both parties, as well as a negative effect on target manager’s career prospects (Fos and Tsoutsoura (2014), Gow, Shin, and Srinivasan (2014), Bebchuk et al. (2017)). Therefore, if \( A \) chooses Fight, the payoffs are:

\[
[\Pi_{A,\text{Fight}}, \Pi_{M,\text{Fight}}] = \left[ \Delta - \tilde{L} - \tilde{F}_A, \Delta - B - \tilde{F}_M \right].
\]  

(2)

If \( A \) chooses Fold, \( M \) ignores the project and the payoffs are:

\[
[\Pi_{A,\text{Fold}}, \Pi_{M,\text{Fold}}] = \left[ -\tilde{L}, 0 \right].
\]  

(3)

To assure each outcome occurs with positive probability in equilibrium and avoid the empirically-implausible pooling equilibrium in Kreps and Wilson (1982) and Milgrom and Roberts (1982), we allow costs to vary from campaign to campaign, perhaps because they

\(^4\)Our model’s equilibrium is identical up to scaling constants under the alternative assumption that \( M \) internalizes a fraction \( 0 < \phi < 1 \) of the benefits, making their net payoff from the project \( \phi \Delta - B \).

\(^5\)Our model’s equilibrium is qualitatively identical when proxy fights have a fixed probability of success. As discussed below, we show that proxy fights in the data produce measurable results in most instances.
are target or interaction specific, according to:

\[
\log(\tilde{L}) \sim N(\mu_L, \tau_L^{-2}),
\]

\[
\log\left(\frac{\tilde{F}_M}{B - \Delta}\right) \sim N(\mu_M, \tau_M^{-2}),
\]

\[
\log(\tilde{F}_A) \sim N(\mu_A, \tau_A^{-2}).
\]

The cost \(\tilde{F}_M\) is scaled by \(B - \Delta\) because, as discussed below, the equilibrium depends only on the ratio \(\frac{\Pi_{M,\text{Fight}}}{\Pi_{M,\text{Settle}}}\) and not on the level of \(\Pi_{M,\text{Settle}}\).

All parameters are common knowledge except \(\mu_A\), which takes one of two values: \(\mu_{agr} < \mu_{caut}\). When \(A\) has \(\mu_A = \mu_{agr}\), they are more likely to fight and we therefore refer to them as aggressive and \(A\) with \(\mu_A = \mu_{caut}\) as cautious. Aggressive \(A\) may have lower average costs associated with proxy fights because they have more of the knowledge and experience necessary to initiate a successful fight. Alternatively, they can be interpreted as intrinsically enjoying the attendant conflict and attention.

\(A\) learns the realization of \(\tilde{L}\) before choosing 13-D or Ignore, and learns the realization of \(\tilde{F}_A\) only after choosing 13-D. \(M\) learns the realization of \(\tilde{F}_M\) prior to deciding whether to Settle. \(A\) knows the distribution of \(\tilde{F}_M\) but not its realization, and similarly \(M\) only knows the distribution of \(\tilde{L}\) and \(\tilde{F}_A\).

3.2. Dynamics

Campaign opportunities arrive exogenously according to a Poisson process with an annualized arrival rate \(\lambda_c\), which we assume is the same for all activists.\(^6\) Upon receiving a campaign opportunity, the above stage game is played instantly. When playing each stage game, \(A\) maximizes their expected payoffs across the current and all future campaign opportunities, using an annual discount factor \(\delta\). Each \(M\) is only targeted once, and so simply

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\(^6\)This assumption and the assumption that campaign costs have the same distribution for both types are important because they focus our model on one-dimensional reputation for proxy fighting. These assumptions are natural to the extent activist campaigns, but not proxy fights, are based on public information and common costs such as price impact. Extending our analysis to allow a second dimension of activist type governing campaign frequency would likely yield additional insights but at the expense of tractability.
maximizes their expected payoffs in the current campaign.\footnote{Targets in our sample experience an average of 1.3 campaigns, with 78\% experiencing only one. By contrast, activists engage in an average of 5.8 campaigns, with 35\% initiating only one.}

The only state variable in the model is $A$’s reputation $r_t$, defined as the probability that $A$ is the aggressive type conditional on their observed track record of campaigns occurring prior to $t$. $A$’s initial reputation is $r_0$, the exogenous unconditional probability they are aggressive. It subsequently evolves as time passes and new campaign opportunities arrive.

The stage game equilibrium depends on $A$’s reputation immediately prior to the campaign opportunity, $r_t$. After the stage game, the econometrician and future target firms observe outcome $o$, a vector of signals correlated with the true outcome ($Settle$, $Fight$, or $Fold$), as detailed in Section 4. Given observed $o$, $A$’s reputation updates to the posterior $r_{t+}$:

$$
  r_{t+}|(o,r_t) = \frac{r_t \cdot \mathbb{P}(o|\mu_A = \mu_{agr}, r_t)}{r_t \cdot \mathbb{P}(o|\mu_A = \mu_{agr}, r_t) + (1-r_t) \cdot \mathbb{P}(o|\mu_A = \mu_{caut}, r_t)}.
$$

\(\text{(7)}\)

Between observed campaigns, $A$’s reputation evolves continuously for two reasons. The first is that the absence of observed campaigns could indicate a campaign opportunity may have arrived but $A$ chose to Ignore it, which we assume is unobserved by future targets. Because cautious $A$ are more likely to choose Ignore, reputation ‘decays’ with each passing moment as it is increasingly likely $A$ ignored an opportunity.

Reputation also evolves between campaigns because there is a chance $A$ will have a change in fund management or investment strategy that results in their type being re-drawn from the unconditional distribution. These type resets arrive according to a Poisson process with an annualized arrival rate $\lambda_r$, and are observed by $A$ but not by $M$. We include them in our model because they cause reputation to mean-revert towards $r_0$, allowing learning in the model to continue indefinitely rather than $r_t$ converging to zero or one. When estimating our model, we find that $\lambda_r > 0$ fits the data significantly better than $\lambda_r = 0$, meaning these type of resets seem to occur in the data.\footnote{Events affecting activists in our sample consistent with type re-draws include Och-Ziff Capital Management’s 2007 IPO, Riley Investment Management’s 2009 IPO, and Raminus Capital merging with the Cowen Group in 2009.} See Appendix A for the relevant formulas.

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Because $A$ knows $r_t$ affects expected payoffs conditional on receiving a campaign opportunity, they internalize the impact of their decisions on future reputation. We quantify this impact using their value function, defined as the expected discounted payoff they will get from all future campaigns conditional on current reputation $r_t$. We write this value function as $V_{\text{caut}}(r)$ for cautious $A$ and $V_{\text{agr}}(r)$ for aggressive $A$, where:

$$V_i(r) \equiv \int_0^\infty \delta^s \lambda_c \mathbb{E}(\Pi_i(r_{t+s})|r_t = r, \mu_A = \mu_i) \, ds,$$

where $\mathbb{E}(\Pi_i(r_{t+s})|r_t = r, \mu_A = \mu_i)$ is the expected payoff to an $A$ of type $i$ for campaigns opportunities at time $t + s$ given $r_t = r$.

3.3. Equilibrium

The stage game equilibrium is specified by five functions of $r_t$: the probabilities that cautious and aggressive type $A$ choose 13-D when a campaign opportunity arises ($d_{\text{caut}}(r_t)$ and $d_{\text{agr}}(r_t)$); the probability $M$ chooses Settle ($y(r_t)$); and the probabilities that cautious and aggressive $A$ choose Fight ($f_{\text{caut}}(r_t)$ and $f_{\text{agr}}(r_t)$).

We solve the stage game equilibrium starting with $A$’s decision to Fight or Fold once $M$ chooses Refuse. $A$ chooses Fight whenever the payoffs from the project and increased reputation outweigh the cost $\tilde{F}_A$:

$$\tilde{F}_A \leq \Delta + \mathbb{E}[V_i(r_{t+})|\text{Fight}] - \mathbb{E}[V_i(r_{t+})|\text{Fold}] \equiv F_i$$

where $r_{t+}$ is $A$’s post campaign reputation and the expectations of value functions are taken across possible observed outcomes $o$ that can occur conditional on the true campaign outcome (Fight or Fold). Equation (9) implies that the type $i$’s probability of fighting satisfies:

$$f_i(r_t) = \Phi^{-1}(\log(F_i - \mu_i),$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution.
M chooses \textit{Settle} when \( p_f(r_t) \), the probability \( A \) fights given their reputation and equilibrium strategy, is sufficiently high relative to their cost of fighting:

\[
\Delta - B \leq (\Delta - B - \tilde{F}_M) p_f(r_t) \Rightarrow \frac{\tilde{F}_M}{B - \Delta} \geq \frac{1 - p_f(r_t)}{p_f(r_t)} \equiv F_M ,
\]

(11)

where \( p_f(r_t) \) is a function of \( d_i(r_t), y(r_t) \), and \( f_i(r_t) \) given in Appendix A.

Equation (11) shows \( M \)’s decision depends on \( \tilde{F}_M \) relative to \( B - \Delta \) rather than in absolute terms. We therefore estimate the properties of \( \frac{\tilde{F}_M}{B - \Delta} \), parameterized by \( \mu_M \) and \( \tau_M \), but have no way of estimating \( B - \Delta \). Equation (11) implies \( M \)’s probability of settling satisfies:

\[
y(r_t) = 1 - \Phi \left( \tau_M^{-1} \left( \log \left( F_M \right) - \mu_M \right) \right) .
\]

(12)

Finally, \( A \) chooses \textit{13-D} when the expected payoffs from the campaign and jump in value function outweigh the cost \( \tilde{L} \):

\[
\tilde{L} \leq - V_i(r_t) + y(r_t) (\Delta + \mathbb{E}[V_i(r_{t+}) | \text{Settle}])
\]

\[
+ (1 - y(r_t)) f_i(r_t) \left( \Delta + \mathbb{E}[V_i(r_{t+}) | \text{Fight}] - \mathbb{E} \left[ \tilde{F}_i \mid \tilde{F}_i < \bar{F}_i \right] \right)
\]

\[
+ (1 - y(r_t))(1 - f_i(r_t)) \mathbb{E}[V_i(r_{t+}) | \text{Fold}] \equiv L_i.
\]

Equation (13) implies that the type \( i \)’s probability of choosing \textit{13-D} satisfies:

\[
d_i(r_t) = \Phi \left( \tau_L^{-1} \left( \log \left( L_i \right) - \mu_L \right) \right) .
\]

(14)

For a given set of parameters, we solve equilibrium strategies and value functions using value function iteration, as detailed in Appendix A.

3.4. No-reputation alternative model

As a benchmark for testing hypotheses and evaluating counterfactuals, we consider an alternative model with the same stage game but no role for reputation. In this alternative
model, $M$ ignores $A$’s track record and assesses the probability that $A$ is the aggressive type as $r_0$. With this restriction, the equilibrium is not the same as the equilibrium in our dynamic model when $r_t = r_0$ because the possibility of changing $r_t$ affects equilibrium behavior. Without this possibility, each stage game follows the same static equilibrium.

Writing $d_{caut}^s$, $d_{agr}^s$, $y^s$, $f_{caut}^c$ and $f_{agr}^s$ for the equilibrium strategies a one-shot stage game, we simplify the cutoff values $\bar{L}_i$ and $\bar{F}_i$ to:

\[
\bar{L}_i^s \equiv y^s \Delta + (1 - y^s) f_i^s \left( \Delta - \mathbb{E} \left[ \tilde{F}_i \mid \tilde{F}_i < F_i^s \right] \right),
\]
\[
\bar{F}_i^s \equiv \Delta.
\]

Based on these cutoffs, we compute the static equilibrium strategies that make Equations (10), (12), and (14) all hold when using $\bar{L}_i^s$ and $\bar{F}_i^s$ in place of $\bar{L}$ and $\bar{F}_i$.

3.5. Model predictions

We illustrate the key predictions of our model with and without reputation in Figure 1. In the static model, instead of viewing reputation as an endogenous state variable changing across activist campaigns, we study how the exogenous likelihood $A$ is aggressive ($r_0$) affects equilibrium outcomes. The first plot of Figure 1 shows both types of $A$ have higher likelihood of initiating campaigns ($d_{caut}^s$ and $d_{agr}^s$) when their exogenous reputation is higher because they are more likely to receive profitable settlements (higher $y^s$), as illustrated the second plot of Figure 1. Finally, exogenous reputation has no impact on either type of $A$’s probability of fighting ($f_{caut}^s$ or $f_{agr}^s$), as illustrated by the third plot in Figure 1, because their decision has no impact on future campaigns in the static model.

The dynamic model carries through these basic implications of the static model but adds two further implications. The first is that both types of $A$ initiate more proxy fights than they do in the static model ($f_{caut} > f_{caut}^s$ and $f_{agr} > f_{agr}^s$). These additional fights arise in cases where a proxy fight’s cost $\tilde{F}_A$ is more than the direct payoff $\Delta$ but justified by the expected increase in future project payoffs ($\mathbb{E} [V_i(r_{t+})|Fight] - \mathbb{E} [V_i(r_{t+})|Fold]$). In this
sense, $A$ invests in their reputation by initiating additional proxy fights at short term losses to extract more settlements in future campaigns. The second result of dynamics in our model is that $A$ initiate more campaigns than they do in the static model ($d_{\text{caut}} > d_{\text{caut}}^a$ and $d_{\text{agr}} > d_{\text{agr}}^a$). Because aggressive $A$ are more likely to choose $13-D$ than cautious $A$, campaigns on average increase reputation. Choosing $13-D$ is therefore another way $A$ can invest in reputation by acting aggressively.

The extent of $A$’s reputation-building incentives depends on the slope of the value function and the degree to which post-campaign reputation improves after each potential outcome. We illustrate these effects in the final two plots of Figure 1. For the parameters presented in this figure, proxy fights substantially increase reputation, settlements moderately increase reputation, and folds slightly increase or decrease reputation depending on pre-campaign reputation. For small values of $r_t$, the value function is much steeper for aggressive $A$ because it is cheaper to build and maintain their reputation in the future. As a result, aggressive $A$ increase their probability of fighting more than cautious $A$ for small values of $r_t$. As $r_t$ approaches one, this relation reverses as reputation increases become more valuable for cautious $A$ because they reduce the necessity of expensive reputation maintenance.

To summarize, the mechanisms by which reputation affects activism in our model are:

1. High reputation activists initiate more campaigns, and all activists sometimes initiate campaigns despite expected losses as an investment in their reputation.

2. Target managers are more likely to settle with high reputation activists.

3. High reputation activists initiate more proxy fights when refused, and all activists sometimes fight despite expected losses as an investment in their reputation.

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9Reputation increases after a campaign where $A$ chooses Fold when the reputation increase coming from choosing $13-D$ outweighs the loss from choosing Fold rather than Fight.
4. Data and Estimation

4.1. Data

We assemble a sample of 4,235 activist campaigns initiated during 1999–2016. We initially identify 35,768 campaigns using 13-D filings collected from the Security and Exchange Commission (SEC)’s Edgar database, and 5,910 campaigns we identify using SharkWatch. Of these we keep 4,221 13-D filings and 3,874 campaigns from SharkWatch in which we successfully match target firms to the Compustat-CRSP Linked data and we identify the activist is a financial institution. We exclude campaigns for which the target security does not pertain to an operating corporation by requiring target CRSP share code be 10, 11, 18, 31, or 71, and dropping campaigns targeting firms with SIC codes 6770 and 6726 (closed-end mutual funds and SPACs, as studied in Bradley et al. (2010)).

Our initial filters result in a sample of 5,756 campaigns, some of which represent multiple activists targeting the same firm in rapid succession in what is known as “wolf pack activism” (see Brav, Dasgupta, and Mathews (2016)). Because this behavior is outside our model, we take several steps to identify a “lead” activist who is the primary aggressor, and attribute each campaign to the lead activist only. First, we classify all campaign initiations by different activists targeting the same firm in the year following the first initiation date as part of a single campaign, which results in 4,235 non-overlapping campaigns, 956 of which feature multiple activists. Second, for the 224 multiple-activist campaigns that involve a proxy fight attributable to a single activist, we select that activist as the lead for the campaign. Third, for the other 732 multiple-activist campaigns, we identify the lead activist as the one who...
first initiates the campaign or, if two activists initiate campaigns on the same day, the activist
with the highest proxy-fight propensity in prior campaigns.

Our main analysis studies a sample of campaigns by hedge funds, who are the primary
focus of empirical literature on activism (see Brav et al. (2008), Brav, Jiang, and Kim (2010))
and who have the institutional structure most favorable to taking the costly actions required
to build and maintain reputation (see Starks (1987), Ackermann, McEnally, and Ravenscraft
(1999), and Stulz (2007)). SharkWatch data indicate directly which activists are hedge funds,
and we identify which 13-D filers are hedge funds by cross-checking the activist name with the
Factset Lionshares holdings data and using one-by-one internet searches. Among the initial
sample of 4,235 campaigns, we find 2,434 activist campaigns by 420 unique hedge funds
targeting 1,889 unique firms. In Section 5.5, we analyze the remaining 1,801 campaigns by
603 unique non hedge fund activists targeting 1,489 unique firms.

4.1.1 Observable outcomes

As described Section 3, after each campaign future targets observe a vector of outcomes
\( o \) that correlate with the actual campaign outcome (Settle, Fight, or Fold):

\[
\begin{align*}
o &= [Proxy, a], \\
a &= [Reorg, Payout, CEO, Board, Acq],
\end{align*}
\]

where \( Proxy \) is a indicator variable for whether the campaign features a proxy fight. The
five variables in \( a \) are indicators for whether the target firm took each of five activist-friendly
actions in the year following campaign initiation: \( Reorg \), which indicates the target firm
announces a reorganization, change in strategic direction, or discontinuation/downsizing of
business; \( Payout \), which indicates the target firm’s quarterly payout (dividends plus stock
repurchases) increases by more than 1% of assets; \( CEO \), which indicates the CEO of the
target firm departs; \( Board \), which indicates a member of the target’s board of directors
departs or a new director is appointed specifically due to activism; and \( Acq \), which indicates
the target firm announces a merger or acquisition, or announces that they seek to sell/divest
a business. All five indicators measure whether the target firm takes these actions in the year
following campaign initiation, and are based on data from Capital IQ Key Developments,
SharkWatch, and Compustat, as detailed in Appendix B.

To isolate the incremental effect of activism on target actions, we estimate the likelihood
they would occur without activism using predictive regressions on a broader universe of all
Compustat firms, as described in Appendix C. We define the expected action vector \( \hat{a} \) as the
fitted value from these regressions for the target at the time of campaign initiation.

We use \( a \) and \( \hat{a} \) to specify how observed outcomes (\( o \)) depend on true campaign outcomes
(\( \text{Settle}, \text{Fight}, \text{or Fold} \)). If the true outcome is \( \text{Fight} \), we observe \( \text{Proxy} = 1 \), and otherwise
we observe \( \text{Proxy} = 0 \). If the true outcome is \( \text{Fight} \) or \( \text{Settle} \), we more-frequently observe
target actions \( a \) equal to one. We specify this increase in action likelihood as:

\[
\mathbb{P}(a_i = 1) = \hat{a}_i + 1(\text{Settle or Fight})\beta_i,
\]

where \( a_i \) is the \( i \)th action in vector \( a \), \( \hat{a}_i \) is its predicted value in the absence of activism,
and \( \beta_i \) is the added probability of action \( i \) during a campaign ending in \( \text{Settle} \) or \( \text{Fight} \). We
discuss our calibration of \( \beta_i \) in Section 4.3.

4.2. Descriptive statistics

Table 1 shows descriptive statistics for our campaign outcome variables. About 14% of
campaigns result in proxy contests, indicating that activists only rarely engage in direct
governance via shareholder vote. Despite this infrequency, Table 1 shows that activists
have a remarkable impact on target behavior even in the 86% of campaigns not featuring a
proxy fight. Targets are much more likely than predicted to initiate corporate restructurings,
change CEOs, change board composition, and engage in mergers or acquisitions. The effect
on board composition is mechanically the strongest, with \( \text{Board} \) equal to one in 25.6% of
campaigns but only 0.4% of the broader Compustat universe, because the Capital IQ code
we use to identify board changes specifically refers to activism-driven changes. These results validate our sample captures most instances of activism, and indicate Board is an excellent measure of campaign success since it rarely occurs by chance. Interestingly, activist targets are only marginally more likely to ‘pay off’ activists by increasing payouts.

Target actions are particularly common in campaigns featuring proxy fights, with Reorg occurring in 32.3% more proxy campaigns than target firm propensity would suggest, Payout in 6.2%, CEO in 17.5%, Board in 67.6%, and Acq in 30.8%. These probabilities indicate proxy campaigns prompt substantial responses from target firms, and support the assumption in our model that target managers find proxy fights privately costly because both CEO and board turnover substantially increase. Combined, we find targets take an average of 1.543 abnormal activist-friendly actions (Ab Actions) in campaigns with Proxy = 1.

Even campaigns not featuring proxy fights are quite successful, with targets taking each action more frequently than our predictive regressions would suggest. The impact of these campaigns is smaller in each case, with average Ab Actions totalling 0.649, around 40% of the total in Proxy = 1 campaigns.

In addition to ex-post campaign outcomes, we use target stock returns around campaign initiations to estimate how much value activists create in their target firms both on average and as a function of reputation. We measure these market reactions using CAR, the [-1, +1] abnormal return for target firm around the day on which the campaign is publicly initiated. Table 1 shows that markets react positively to activist campaign initiations, with share prices increasing by an average of 2.8%. This is consistent with evidence in prior literature (e.g., Brav et al. (2008) and Collin-Dufresne and Fos (2015)) and our model’s assumption that activist campaign outcomes are either positive or neutral for shareholders, meaning the initiation of a campaign is positive news in expectation.

4.3. Estimation

We estimate our model by choosing the parameters $\theta$ that maximize the model-implied likelihood of observed data. This estimator differs from the SMM methodology used fre-
sequently in estimating dynamic corporate finance models.\textsuperscript{13} SMM is not well-suited to our setting because any reasonable set of moments would employ a reputation measure, which itself is parameter-dependent and therefore cannot be computed directly in the data. Furthermore, unlike many dynamic corporate finance models, our model’s likelihood function can be efficiently computed.

Given a set of parameters, we begin by solving for equilibrium strategies and value functions as described in Section 3.3. Using these strategies, we compute each activist’s reputation $r_t$ for each day in the sample starting with their first campaign initiation, with reputation evolving as described in Section 3.2. We use this panel of $r_t$ to compute the conditional likelihood of each observed campaign as follows:

$$L_c(\theta) = L_c^{gap}(\theta) \cdot L_c^{13-D}(\theta) \cdot L_c^{car}(\theta) \cdot L_c^{outcome}(\theta),$$

where $L_c^{gap}(\theta)$ is the probability the activist initiates no campaigns until the date of their next 13-D, $L_c^{13-D}(\theta)$ is the probability the activist got a campaign opportunity and chose 13-D on the date of campaign $c$, $L_c^{car}(\theta)$ is likelihood of the target stock’s reaction to the news of a campaign ($CAR$), and $L_c^{outcome}(\theta)$ is the likelihood of the observed outcomes conditional on the activist choosing 13-D. Each of these likelihoods depends on $r_t$, as detailed in Appendix D. Because $r_t$ is the only state variable in our model, the observations are conditionally independent. We assume $CAR$ is conditionally normally distributed, with mean equal to the expected value created for shareholders given $r_t$, and standard deviation $\sigma_{car}$ equal to 8.99%, the standard deviation of $CAR$ in our sample.

To make our results easier to interpret, we map the means of log costs ($\mu_L, \mu_M, \mu_{caut}$, and $\mu_{agr}$) to what they imply for equilibrium strategies when $A$’s reputation is zero. We define $d_{caut,0}, y_0, f_{caut,0}$, and $f_{agr,0}$ as the probabilities a cautious $A$ chooses 13-D, $M$ chooses Settle, a cautious $A$ chooses Fight, and an aggressive $A$ chooses Fight, respectively, given $r_t = 0$.

\textsuperscript{13}See Strebulaev and Whited (2012) for a review of the SMM methodology and its applications, and Bazdresch, Kahn, and Whited (2017) for evidence on SMM’s small sample properties.
In this case, reputation is irrelevant and there is a one-to-one mapping between these four probabilities and the corresponding means of log costs (see Appendix D).

Like all maximum likelihood estimates, our formal identifying assumption is that our model correctly describes the data generating process, allowing us to estimate model parameters from observed data via the apparent functional form of the relations among variables. Econometrically, this requires that the likelihood function have a unique maximum at the true parameter values, and not be ‘too flat’ around this maximum. Economically, it requires that changes in each parameter generates predicted changes in the data that are at least partially distinct from one another.

With these identification requirements in mind, we assume values for two additional parameters for which we have no hope of estimating in the data, activists’ discount factor $\delta$ and the arrival rate of campaign opportunities $\lambda_c$. We cannot distinguish empirically between a high value of $\delta$, which makes activists initiate more campaigns and proxy fights as investments in reputation, from higher values of campaign cost precision $\tau_L$ and manager proxy cost precision $\tau_A$, which have the same two effects, respectively. We therefore base our estimation on the assumption that $\delta = 0.9$.\textsuperscript{14} Similarly, we cannot distinguish empirically between a high arrival rate $\lambda_c$, which makes observed campaigns occur more frequently, and a high zero-reputation campaign initiation rate $d_{caut,0}$, which has the same effect. We therefore assume a $\lambda_c = 10$, which is sufficiently high so that the upper bound on $13$-D frequency ($d_i(r_i) \leq 1$) is far from binding.\textsuperscript{15}

To minimize the number of estimated parameters, we calibrate $\beta_i$, the added probability of action $a_i$ due to a successful campaign. Equation (19) shows $\beta_i$ equals the average $a_i - \hat{a}_i$ in campaigns featuring a proxy fight, which we present in Table 1. We summarize these values, and the values of $\delta$ and $\lambda_c$, in Panel B of Table 2.

\textsuperscript{14}This is a common problem when structurally estimating dynamic models in corporate finance, and $\delta = 0.9$ is a standard value to assume (e.g. in Taylor (2010)). In untabulated tests, we find our main conclusions are robust to using $\delta = 0.85$ instead.

\textsuperscript{15}In untabulated tests, we find $\lambda_c = 5$ results in proportionally scaled values of $d_i(r_i)$ but does not affect our main conclusions.
We estimate the remaining 10 parameters using maximum likelihood:

$$\theta = [\Delta, d_{caut,0}, \tau_L, y_0, \tau_M, f_{caut,0}, f_{agr,0}, \tau_A, r_0, \lambda_r],$$

(21)

as summarized in Panel A Table 2. Informally speaking, we identify model parameters as follows. We identify the zero-reputation campaign probability \(d_{caut,0}\), settle probability \(y_0\), and cautious A fight probability \(f_{caut,0}\) using average campaign frequency, \(Ab\) \(Actions\), and \(Proxy\) when \(r_t\) is low, respectively. We identify the zero-reputation aggressive A fight probability \(f_{agr,0}\) using average \(Proxy\) when reputation is high. We identify the precisions of random campaign costs \((\tau_L)\), M’s cost of fighting \((\tau_M)\), and A’s cost of fighting \((\tau_A)\) jointly using the shape of the relations between \(r_t\) and campaign frequency, \(Ab\) \(Actions\), \(CAR\), and \(Proxy\). We identify initial reputation \(r_0\) using the outcomes of activists’ first campaigns, as summarized in Table 1, as well as the apparent prevalence of aggressive A. We identify the arrival rate of management changes that re-draw type, \(\lambda_r\), using the degree of persistence in observed outcomes, particularly for extremely low or high \(r_t\) activists. Finally, we identify the value created by successful campaigns, \(\Delta\), by combining average \(CAR\) with the estimated success rate of campaigns. We quantify these informal identification arguments by showing the impact of changes in parameters on model-implied moments in Appendix D.

Our maximum likelihood approach does not explicitly identify each parameter using any one moment or any set of moments, but instead uses the full joint distribution of campaign frequency, market reactions, and campaign outcomes. The model can informally be viewed as ‘overidentified’ because we ask the same set of parameters to generate the reputation measure as well as its relation with campaign frequency and three partially-independent outcome measures (\(a\), \(CAR\), and \(Proxy\)). As a result, no combination of parameters can explain all the features of the data. We discuss which aspects of the data our model fits well and which it struggles to match in Section 5.3.
5. Results and Counterfactuals

5.1. Equilibrium results and hypothesis tests

Panel A of Table 2 presents our estimates of model parameters along with confidence intervals based on likelihood ratio tests, as detailed in Appendix D. Intuitively, these intervals represent the regions outside which our model fits the data significantly worse even if we freely re-estimate the other nine parameters.

We find that the projects activists demand add \( \Delta = 6.62\% \) of market capitalization to their targets when their campaigns succeed. Private costs to target managers of these projects are sufficiently large relative to the costs and likelihood of proxy fights that they only settle in \( y_0 = 21.82\% \) of campaigns when the activist is sure to be the cautious type. We estimate \( r_0 = 2.05\% \) of activists are aggressive types who fight \( f_{agr,0} = 48.03\% \) of the time when their demands are refused and reputation is not a concern, compared to only a \( f_{caut,0} = 11.10\% \) baseline fight rate for cautious types. Activist type resets arrive at a rate of \( \lambda_r = 0.19 \) per year. Note that type resets do not necessarily imply type changes because we estimate most activists are cautious and remain cautious after their type is re-drawn.

Our estimated parameters imply the mean campaign cost \( (\bar{L}) \) is 5.44\% of the activist’s position in the target, while the mean proxy fight cost \( (\bar{F}_A) \) is 8.68\% for aggressive \( A \) and 19.44\% for cautious \( A \). These averages are substantial relative to the return from a successful campaign \( (\Delta = 6.62\%) \), resulting in activists initiating campaigns and proxy fights only when cost realizations are unusually low. The relative size of average activist costs also illustrate the importance of reputation-building incentives, which allow activists to sometimes initiate campaigns and proxy fights despite the costs exceeding single-campaign benefits.

For a given set of no-reputation parameters \( d_{caut,0}, y_0, f_{caut,0}, \) and \( f_{agr,0} \), the precision parameters \( \tau_L, \tau_M, \) and \( \tau_A \) determine how agents behave when reputation is strictly positive. Large values of \( \tau_L \) and \( \tau_M \) indicate stronger relations between reputation and campaign initiation and settlement decisions, respectively. Large values of \( \tau_A \) indicate more reputation-
seeking fights. Small values of these precisions indicate agents follow mixed strategies independent of their reputation. We find that all three precisions are positive and statistically distinct from zero, indicating that constraining our model to ignore reputation at any of the three stages results in significantly worse fit. We illustrate the economic significance of these precisions in Figure 1, which presents estimated equilibrium strategies as a function of reputation, as described in Section 3.5.

We formally test whether reputation significantly affects equilibrium outcomes using two constrained versions of our model: a no reputation framework in which targets do not use past campaigns to assess the activist type, and a full information framework in which each activist’s type is common knowledge. For each framework, we re-estimate the model to find parameters that best fit the data. In the no reputation framework, each campaign is played independently of other campaigns using the static equilibrium described in Section 3.4 with the unconditional reputation \( r_0 \) applying in all campaigns. From our perspective, this means all stage games follow the same mixed strategy equilibrium with a \( A \) choosing 13-D with probability \( d_{norep} \), \( M \) choosing Settle with probability \( y_{norep} \), and \( A \) choosing Fight with probability \( f_{norep} \). While we can identify these equilibrium probabilities, we cannot identify the full set of parameters \( \theta \) in a no-reputation world because many \( \theta \) generate the same static game equilibrium. One of many equivalent formulations for any no-reputation equilibrium features \( r_0 = 0 \), meaning we can estimate the no-reputation model with only four parameters: \( \Delta, d_{caut,0}, y_0, \) and \( f_{caut,0} \), with other parameters not being identified.

Panel C of Table 2 presents our estimates of the no reputation model. We find that activists choosing 13-D with probability 9.94%, managers choosing Settle with probability 28.05%, and activists choosing Fight with probability 19.87% fit the data best. These probabilities are higher than the zero-reputation strategies in our baseline estimation because they capture average behavior in our whole sample instead of the behavior of an activist with \( r_t = 0 \). As Figure 1 illustrates, campaign frequency, settlement, and fighting are all much more frequent when \( r_t > 0 \) in our dynamic model than when \( r_t = 0 \).
Despite fitting the data as well as possible on average, the no-reputation parameters result in a much lower likelihood of the observed data than our more general model because, as we document below, our reputation measure strongly predicts campaign frequency and outcomes. We therefore find a high Wilks (1938) likelihood ratio $\chi^2$ statistic, with a $p$-value of 0.00%, and can clearly reject the no reputation hypothesis.

An second alternative hypothesis is that targets have complete information about which type of activist they are facing. Like the no reputation hypothesis, the full information hypothesis removes reputation-building incentives. However, unlike the no reputation hypothesis, each stage game does not feature the same equilibrium strategy. Instead, each game is played according to the $r_0 = 0$ static equilibrium for cautious $A$, and the $r_0 = 1$ static equilibrium for aggressive $A$. To make the full information model estimable by econometricians who do not directly observe activist type, we assume activist types do not change and assign each activist the type that maximizes the likelihood of their full-sample set of campaign outcomes. We therefore identify the full set of parameters $\theta$ except for $\tau_A$ (because reputation is never between 0 and 1) and $\lambda_r$ (because activist types do not change).

We find that the full information model fits the data best when cautious $A$ choose 13-D 9.12% of the time and Fight 12.36% of the time, while aggressive $A$ choose 13-D 65.9% of the time and Fight 64.15% of the time, and $M$ settles with cautious $A$ 29.5% of the time and aggressive $A$ 40.8% of the time.\textsuperscript{16} Aggressive $A$ are less common ($r_0 = 0.85\%$ vs 2.05\%) in the full information estimates. While the full information hypothesis fits the data better than the no reputation hypothesis, it is still strongly rejected because our baseline reputation model allows for campaign frequency and success to vary within-activist as their reputation changes. This possibility fits the data better than ascribing, even with the benefit of full-sample hindsight, each activist as consistently playing the same equilibrium.

\textsuperscript{16}Aggressive $A$’s probability of choosing 13-D, and $M$’s probability of settling with aggressive $A$, are computed from full-information $d_{caut,0}$, $\tau_L$, $y_0$, and $\tau_M$. 

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5.2. Reputation in the data

Our estimation procedure produces pre- and post-campaign reputation measures \( r_t \) and \( r_{t+} \) for all campaigns in our sample, as summarized by Table 3. Because aggressive activists are rare unconditionally \( (r_0 = 2.05\%) \), reputation is extremely positively skewed across campaigns. Most pre-campaign reputations are negligible, with a median of only 0.55\%. Occasionally, though, activists in our sample establish strong reputations, and when they do they initiate more campaigns, making the mean pre-campaign \( r_t \) equal to 10.81\%.

Panel B of Table 3 shows the top 25 activists by average model-based reputation. It contains many of the best-known activist hedge funds, including Third Point, Elliot Associates, and Valueact. The two standouts, though, are Starboard Value and Icahn Enterprises. Both have 77 campaigns in our sample, around 30 proxy fights, generate unusually many target actions, and have average pre-campaign reputations above the 90th percentile of the overall distribution. Figure 2 shows these the evolution of these activists’ reputation through our sample, both of which are above 75\% for the past decade and peak above 99\%. The third plot of Figure 2 also shows the evolution of reputation for Loeb Partners, who has only initiated one proxy fight, has a low reputation for most of the sample, and extracts many fewer settlements than Icahn Enterprises and Starboard Value.

As illustrated by Figure 2, reputations are persistent but decay somewhat rapidly in the absence of campaigns. One reason for this decay is that activist types are redrawn at a rate of \( \lambda_r = 0.19 \) per year. Consistent with this feature, Figure 2 shows activist behavior appears to have occasional ‘regime shifts’ whereby an activist with consistently high or low reputation suddenly changes behavior and reputation. Both Icahn Enterprises and Starboard Value were much less frequent and successful activists, and as a result had reputation below 20\%, until around 2005, at which point their behavior changed and reputation grew. Another example of this phenomenon is Riley Investment Management, who Figure 2 illustrates built a strong reputation from 2005–2009 and then suddenly became inactive, possibly due to their parent company’s 2009 IPO, initiating only one additional campaign in late 2013.
5.3. Effects of reputation and model fit

We assess our model’s fit and measure the effects of reputation by estimating model-implied equilibrium strategies for each campaign in our sample, computing what these strategies imply for the distribution of outcomes, and comparing these predictions to the outcomes observed in the data. To study the first stage of our activism game, we compute each activist’s reputation $r_t$ for all days in our sample, including days without campaign initiations.17 Using this panel of $r_t$, we compute the model-implied strategies for both types of activist, $d_{caut}(r_t)$ and $d_{agr}(r_t)$, giving us the probability we observe a 13-D on each activist-day. We then compare these model-implied 13-D probabilities to observed 13-D frequencies both on average and in subsamples sorted by $r_t$.

Panel A of Table 4 shows that our model predicts activists initiate an average of 1.00 campaigns per year, and that high reputation activist-days (those with $r_t > 50\%$) result in campaign initiations at a rate of 3.50 per year, six times as frequently as the 0.58 per year rate for low reputation activist-days (those with $r_t < 0.50\%$). The data reveal nearly identical frequencies to our model’s predictions both on average and for extreme $r_t$.

Our structural approach also yields estimates for the parameters governing the distributions of costs and payoffs for activists, allowing us to estimate the fraction of observed campaigns initiated despite expected losses in the campaign itself as an investment in reputation. For each observed campaign in the sample, we compute the likelihood of drawing $\bar{L}$ low enough to initiate a campaign in the dynamic model and compare this to the likelihood of drawing $\bar{L}$ low enough the expected profit from the individual campaign, ignoring changes in the value function, is positive. From this comparison, we estimate 80.08% of 13-D decisions in our sample had positive expected profits in the coming campaign, while the remaining 19.92% were due to reputation-building incentives.

Panel B of Table 4 summarizes strategies, observable outcomes, and motivations pertaining to settlement and fighting decisions conditional on a campaign initiation. For this panel,

\footnote{See Appendix D for details on how we handle activists only present in part of our sample.}
we sort observed campaigns by pre-campaign reputation $r_t$. Our model predicts high reputation activists receive settlements 44.11% of the time compared to only 23.86% of the time for low reputation activists, as depicted in the second plot of Figure 1. This translates into a strong relation between $r_t$ and the average AbActions in campaigns without a proxy fight, which our model predicts varies from 0.41 for low $r_t$ campaigns to 0.91 for high $r_t$ campaigns. Our model fits the data well for medium and high reputation activists but underestimates the success of low reputation activists in non-proxy campaigns.

Settling and fighting decisions in our fitted model combine to predict a strong relation between $r_t$ and both CAR and AbActions in all campaigns. The data strongly supports the predicted directions of these relations, but imperfectly matches the predicted quantities. Both low and high $r_t$ activists receive more average AbActions than predicted by our model, with only medium reputation campaigns matching the model closely. The model fits average CAR quite well (2.80% vs. 2.82%), but the difference between high and low reputation activists’ average CAR is smaller than predicted by the model (1.81% instead of 2.36%).

Finally, we estimate that 81.17% of observed proxy fights were immediately profitable, while the remaining 18.83% were taken at a loss to the activist as an investment in reputation. This fraction is slightly lower than the corresponding fraction of campaign initiations (19.92%) despite proxy fights having a larger impact on post-campaign reputation because our estimates indicate proxy fighting decisions are noisier than campaign initiation decisions ($\tau_A < \tau_L$). As a result, random costs of fighting $\tilde{F}_A$ are less likely to fall in the region where reputation-building incentives are decisive.

As an alternative illustration of the the magnitude of our main empirical findings and quality of our model’s fit, we use linear regressions to compare observed relations between $r_t$ and campaign frequency and outcomes to those predicted by the model. These regressions abandon the structure of our model, which predicts non-linear relations, and so should be viewed as providing additional descriptive moments rather than as formal hypothesis tests. However, they offer several advantages over the summary statistics in Table 4: they allow us
to compute standard errors clustered by activist to get a sense for which dimensions of the data the model fits ‘closely enough,’ compare our results to other empirical work on activism, and control for other potentially-relevant activist characteristics.\footnote{Other structural papers using reduced form regressions on structurally-estimated parameters to illustrate results include DeAngelo, DeAngelo, and Whited (2011) and Li, Whited, and Wu (2016).}

We find $r_t$ significantly predicts 13-D, AbActions, CAR, and Proxy in linear regressions with year fixed effects and standard errors clustered by activist, as presented in Panel A of Table 5. With the exception of Proxy, the magnitude of the estimated coefficients are within one standard error of the model-predicted magnitudes, suggesting the model fits fairly well along these dimensions. Echoing the results in Table 4, we find the relation between $r_t$ and Proxy is weaker in the estimated model than in the data. No choice of parameters perfectly fits all these relations because changing a parameter such as $\tau_A$ to make the model-implied relation between $r_t$ and Proxy stronger would simultaneously strengthen the relations between $r_t$ and CAR and AbActions, both of which are already a bit stronger in the fitted model than the data. See Appendix D for more detail on how parameters changes affect different dimensions of fit.

Tables 4 and 5 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 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.
In Panel B of Table 5, we repeat our regression analysis while including several time-varying activist characteristics as controls. Two variables, *Prior Campaigns* and *Top HF*, mimick the experience and reputation measures used in Boyson, Ma, and Mooradian (2016) and Krishnan, Partnoy, and Thomas (2016), respectively. The remaining controls represent potential confounding effects for our results in Panel A, for example the possibility that high reputation activists are more successful because they take larger positions in their target firms. We find that the coefficients on \( r_t \) remain economically and statistically significant in each regression, with the coefficient magnitudes slightly increasing in four of the five specifications. The alternative measures have some success in predicting 13-D and *Fight* incremental to \( r_t \), but have little to add in forecasting campaign success as measured by *Ab Actions* and *CAR*. These results indicate our model-based reputation measure \( r_t \) summarizes most of the relevant information contained in other natural measures.

### 5.4. Counterfactuals

Having analyzed the role of reputation in equilibrium activism, we now estimate how this equilibrium would change in a world without reputation.\(^{19}\) We consider three counterfactuals, each a variation of the static model described in Section 3.4. The first requires targets ignore past behavior and use \( r_0 \) as the probability the activist is aggressive. In this ‘no reputation’ counterfactual, activists and targets play the same strategy in every campaign opportunity: the static equilibrium strategy when \( r_0 = 2.05\% \). The second counterfactual we consider sets \( r_0 = 0 \), removing the possibility of aggressive \( A \) from the model. In this ‘no aggressive \( A \)’ counterfactual, cautious \( A \) and \( M \) play their zero-reputation strategies \( d_{caut,0}, y_0 \), and \( f_{caut,0} \). In the third counterfactual, \( M \) observes \( A \)’s type directly, removing the role for reputation and learning. In this ‘full information’ counterfactual, the \( r_t = 0 \) equilibrium prevails for all of cautious \( A \)’s opportunities, while the \( r_t = 1 \) equilibrium prevails for all of aggressive \( A \)’s opportunities, neither of which have reputation-building.

\(^{19}\)This analysis differs from the hypothesis tests described in Section 5.1 because instead of estimating a distinct parameterization that best fits the data, we retain the relevant estimated parameters from our dynamic model and assess how outcomes change without reputation.
We estimate equilibrium behavior and payoffs in the baseline model and each counterfactual by simulating 1000 samples as detailed in Appendix D. Table 6 presents average behavior at each stage of the game and average payoffs to target shareholders and activists per campaign opportunity.\(^{20}\) We find cautious and aggressive A choose 13-D less frequently in all three counterfactuals because they no longer have reputation-building motives. For cautious A, this effect is stronger in the no aggressive A and full information counterfactuals because M knows A is cautious and therefore infrequently settles. However, even when cautious A’s type remains unknown in the no-reputation counterfactual, they still initiate fewer campaigns than in our baseline model due to the absence of reputation-building incentives.

Conditional on campaign initiation, we also find targets would be less likely to settle without reputation. In our baseline model, managers settle in 27.44% of campaigns, compared to 23.81%, 21.82%, and 22.31% in the three counterfactuals. Targets settle less frequently without reputation because activists fight less frequently. For all three counterfactuals, because reputation-building incentives are absent, cautious A chooses Fight \(f_{caut,0} = 11.10\%\) of the time, and aggressive A \(f_{agr,0} = 48.03\%\) of the time, both less than their likelihood of fighting in the dynamic equilibrium.

Combining these effects, Table 6 shows average payoffs for target shareholders per campaign opportunity would decline by at least 48% in all three counterfactuals. Target shareholders receive nothing if the project does not occur, and a proportional share price increase of \(\Delta\) if it does. The average payoff to target shareholders is therefore proportional to the probability the project occurs, which requires that A chooses 13-D and either M chooses Settle or A chooses Fight. Because all three of these choices are less likely without reputation, Table 6 shows that for each type of activist, and overall, average target shareholder payoffs would decline without reputation.

Average activist payoffs also decline without reputation because activists extract fewer settlements. Cautious A suffer more in the counterfactuals without aggressive A or with

\(^{20}\)Because we only estimate the distribution of target managers’ cost of proxy fights (\(\hat{F}_M\)) relative to their net private costs of the project \((B - \Delta)\) we cannot quantify managers’ payoffs in absolute terms.
full information because $M$ knows the activist’s type and therefore settles even less than in the no reputation counterfactual. Aggressive $A$, by contrast, benefit from the full information counterfactual because $M$ always knows their type and chooses Settle more frequently without the necessity of costly reputation-building.

Comparing the average payoffs of activists and target shareholders illustrates how stark the free-rider problem is in this setting. The private costs of activism are sufficiently large in our baseline estimate that activists’ average net returns per campaign opportunity are less than a fifth of average returns for their targets. The size of these costs and their impact on the net performance of activist hedge funds is consistent with the evidence in Clifford (2008), Brav et al. (2008), and Gantchev (2013).

5.5. 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 Table 7 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 $Ab\text{Actions}$, $CAR$, 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 $Ab\text{Actions}$. 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 Ab Actions 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, Ab Actions 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 Table 7, 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 Table 7. 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.
6. Conclusion

This paper argues that reputation for proxy fighting helps explain why activism is both common and successful despite the large private costs and infrequent proxy fights observed empirically. To support this claim, we estimate a dynamic model in which activists engage target firms in a series of campaign opportunities. Each target computes the activist’s reputation, defined as the probability they are an aggressive type that has a lower average cost of proxy fighting. In our estimated model and empirical tests, we find our model-based reputation measure significantly predicts campaign frequency, market reactions, target responses, and the frequency of proxy fights. Using estimated parameters and the structure of the model, we find that 20% of observed campaign initiations and 19% of proxy fights are due to reputation-building incentives, and that activism would produce 48% less value value for target shareholders in a counterfactual world without reputation.

Activists in our model differ only by their average cost of proxy fighting. While this allows us to focus succinctly on the effects of reputation for proxy fighting, other forms of activist heterogeneity could give rise to reputations for frequent campaigning, identifying positive NPV projects, negotiating advantageous settlements, and many other skills. Future research could examine these possibilities using a similar approach to this paper. More broadly, our methodology could potentially be used to estimate dynamic reputation models in many areas of finance and economics.
Appendix A. Model Details

A.1. Reputation dynamics between campaigns

Between campaigns, \( r_t \) evolves according to:

\[
\frac{dr_t}{\lambda_c(1-d_{caut}(r_t))(1-r_t) + \lambda_c(1-d_{agr}(r_t))r_t + (1-\lambda_c)r_t}dt + (r_0 - r_t)\lambda_c dt.
\]

The evolution due to type resets is the product of their arrival rate \( \lambda_r \) with the change in reputation that occurs conditional on arrival, \( r_0 - r_t \). The decay due to the absence of campaigns affects reputation in proportion to:

\[
\begin{align*}
\Pr(\text{agr}|r_t, \text{no camp.}) - r_t &= \frac{\Pr(\text{no camp.}|r_t, \text{agr})r_t}{\Pr(\text{no camp.}|r_t, \text{agr}) + \Pr(\text{no camp.}|r_t, \text{caut})(1-r_t)} \\
&= \frac{[(1-d_{agr}(r_t))\lambda_c + (1-\lambda_c)r_t + [(1-d_{caut}(r_t))\lambda_c + (1-\lambda_c)](1-r_t)] - r_t}{(1-d_{agr}(r_t))\lambda_c + (1-\lambda_c)r_t + [(1-d_{caut}(r_t))\lambda_c + (1-\lambda_c)](1-r_t)},
\end{align*}
\]

which simplifies to the value given in Equation (22).

A.2. Numeric solution and value function iteration

We solve the model numerically using value function iteration on a \( 106 \times 1 \) grid of \( r_t \):

\[
r = [0, \Phi([-6, -5, -4, -3.5, -3.43, -3.36, \ldots, 3.36, 3.43, 3.5, 4]), 1],
\]

where \( \Phi \) is the standard normal CDF. We use a denser grid of \( r_t \) near zero because very small \( r_t \) are common in equilibrium.

In specifying the cutoff for \( \tilde{F}_M \) in Section 3, we omitted the formula for \( p_f(r_t) \), the probability \( A \) chooses \( \text{Proxy} \) conditional on pre-campaign reputation \( r_t \) and choosing 13-D, but not conditional on \( A \)'s type. This formula is:

\[
p_f(r_t) = \frac{r_t d_{agr}(r_t)f_{agr}(r_t) + (1-r_t)d_{caut}(r_t)f_{caut}(r_t)}{r_t d_{agr}(r_t) + (1-r_t)d_{caut}(r_t)}
\]

We use value function iteration to find equilibrium strategies \( d_i, y, \) and \( f_i \) along with value functions \( V_i \) as follows:

1. Find \( d_i, y, \) and \( f_i \) assuming a flat value function \( V_i(r) = 0 \) by numerically searching for values that satisfy Equations (10), (12), and (14).

2. Find the reputation updating function both between campaigns and after campaigns. Equation (22) specifies how \( r_t \) evolves between campaigns given model parameters and equilibrium \( d_i(r_t) \). After an observed campaign at \( t \), reputation jumps to \( r_{t+} \) according
to Equations (7) and (19) combined with Bayes’ rule as follows:

\[
rt+((\text{Proxy} = 1, rt = r) = \frac{rd_{agr}(r)f_{agr}(r)}{rd_{agr}(r)f_{agr}(r) + (1 - r)d_{caut}(r)f_{caut}(r)}
\]

\[
rt+((\text{Proxy} = 0, rt = r) = \frac{rd_{agr}(r)\mathbb{P}(\text{Settle}|a, r)}{rd_{agr}(r) + (1 - r)d_{caut}(r)}
\]

\[
+ \frac{rd_{agr}(r)(1 - f_{agr}(r))\mathbb{P}(\text{Fold}|a, r_t)}{rd_{agr}(r)(1 - f_{agr}(r)) + (1 - r)d_{caut}(r)(1 - f_{caut}(r))}.
\]

The posterior probabilities a campaign was settled given Proxy = 0 are:

\[
\mathbb{P}(\text{Settle}|a, rt = r) = \frac{\mathbb{P}(a|\text{Settle}, r_t)\mathbb{P}(\text{Settle}|r_t)}{\mathbb{P}(a|\text{Settle}, r_t)\mathbb{P}(\text{Settle}|r_t) + \mathbb{P}(a|\text{Fold}, r_t)\mathbb{P}(\text{Fold}|r_t)},
\]

\[
\mathbb{P}(\text{Fold}|a, rt = r) = 1 - \mathbb{P}(\text{Settle}|a, r_t),
\]

which can be computed using Equation (19) combined with equilibrium strategies.

3. Find \( V_i \) using equation:

\[
V_i = \mathbb{E}(\Pi_i) + \delta^{1/365} \Sigma_i V_i,
\]

\[
\Rightarrow V_i = (I_{106} - \delta^{1/365} \Sigma_i) \mathbb{E}(\Pi_i)
\]

where \( V_i \) is a 106 \times 1 vector of \( V_i(r_t) \) values for \( r_t \in r \), \( \mathbb{E}(\Pi_i) \) is a 106 \times 1 vector expected per-day profits for \( A \) with type \( i \), \( \delta \) is the annualized discount factor, \( \Sigma_i \) is a 106 \times 106 transition probability matrix describing the likelihood of reputation transitions in a single day, and \( I_{106} \) is the identity matrix. We compute this transition probability matrix using Equation (22) discretized daily, the distribution of possible observed outcomes \( o \) conditional on a campaign occurring (from Equation (19)), and the post-campaign reputations \( r_t \) each \( o \) implies (from Step 2).

4. Repeat Steps 1–3 using the value function found in Step 3 and compare the resulting value function to the last one found. Repeat this iteration until the sum across \( r \) of changes in the value function is less than 0.01.

**Appendix B. Variables Definitions**

**B.1. Activist reputation and related measures**

These variables are constructed using form 13-D and Proxy filings data from the SEC’s Edgar database which we access via the WRDS SEC Analytics tool, SharkWatch, and our estimation which we describe in Section 4.3.

- **Prior Campaigns** is the number of previous activist campaigns initiated by the activist. This measure approximates the experience measure in Boyson, Ma, and Mooradian (2016).
- **\( r_t \)** is our estimate of the activist’s pre-campaign reputation, which we describe in Section 4.3.
• $r_{t+}$ is our estimate of the activist’s post-campaign reputation, which we describe in Section 4.3.

• Top HF is an indicator equal to one for activist hedge funds ranked in the top quintile by the trailing year average position size for all activist campaigns. This measure approximates the main reputation measure in Krishnan, Partnoy, and Thomas (2016).

B.2. Other Activist Characteristics

These variables are constructed using data from CRSP and Thomson Reuters. For the small minority of activists with no precise date and mgrno identifier match, we use data from an additional one quarter prior or one quarter later.

• Log Portfolio Size is the log of the total market cap of all positions, from form 13-F, held by the activist at the quarter-end prior to the initiation of each campaign.

• Portfolio Turnover is the trailing one-year average quarterly portfolio turnover, as defined in Gaspar, Massa, and Matos (2005).

• Stake Size is the share of the target firm’s shares outstanding held by the activist as of the first quarter after the initiation of each campaign, from form 13-F. In a handful of cases with no match we assign the sample average of roughly 7%.

B.3. Activist campaign outcome measures

These variables are constructed using form 8-K data from Capital IQ Key Developments, form 13-D and Proxy filings data from the SEC’s Edgar database which we access via the WRDS SEC Analytics tool, cash flow and balance sheet data from Compustat, as well as CRSP and SharkWatch.

• 13-D is an indicator equal to one on activist-days in which a campaign is initiated.

• Ab Actions is Actions minus $\widehat{\text{Actions}}$.

• Actions is the sum of Acq, Board, CEO, Payout, and Proxy.

• $\widehat{\text{Actions}}$ is the sum of predicted values for Acq, Board, CEO, Payout, and Proxy in the absence of activism, computed as detailed in Appendix C.

• Acq is an indicator equal to one if the target firm announces a merger or acquisition, or announces that they seek to sell/divest a business, within the year following the initiation of each campaign, which we define using Capital IQ codes 1 and 80.

• Board is an indicator equal to one if a member of target firm’s board of directors departs or a new director is appointed due to activism, within the year following the initiation of each campaign, as indicated by Capital IQ code 172 or SharkWatch.

• CAR is the three-day [-1,+1] market-adjusted return for the target firm around the day in which each activist campaign is initiated.

• CEO is an indicator equal to one if the CEO of the target firm departs within the year following the initiation of each campaign, which we define using Capital IQ code 101 or SharkWatch.

• Payout is an indicator for a company’s quarterly payout (dividends plus stock repurchases) increasing by more than 1% of assets (vs. the prior year) within the year following the initiation of each campaign, which we measure using financial statement data from Compustat.
• *Proxy* is an indicator equal to one if the activist initiates a proxy fight in the year following campaign initiation, as detailed in Section 4.1.

• *Reorg* is an indicator equal to one if the target firm announces a reorganization, change in strategic direction, or discontinuation/downsizing of business, within the year following the initiation of each campaign, which we define using Capital IQ codes 21 and 63 or SharkWatch.

### B.4. Target firm characteristics

These variables are constructed using data from Compustat, CRSP, and Thomson Reuters.

• **1 Year Return** is the cumulative total return over the year prior to the campaign initiation date.

• **Book to Market** is the equity book-to-market ratio: book equity from Compustat divided by CRSP market capitalization.

• **Capex/Assets** is the trailing year’s total capital expenditures from the cash flow statement divided by lagged total assets.

• **EBIT/Assets** is the trailing year’s total earnings before interest and taxes from divided by lagged total assets.

• **Log Size** is the natural log of CRSP market capitalization.

• **Net Leverage** is total debt, net of cash, divided by lagged total assets.

• **Inst Investors** is the number of 13-F filers holding the stock in the most recent quarter.

• **Payout/Assets** is the trailing year’s total dividend payments and stock repurchases (from the cash flow statement) divided by lagged total assets.

### Appendix C. Target Firm Actions Propensity Measure

In this Appendix we outline 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 (34) outlines each regression:

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

(34)

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$_{j,t}$*.

Table C1 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).

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21We define in detail how we calculate each of the actions and characteristics in Appendix B.
Table C1: 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: Reorg$_{j,t+4}$, for whether firm $j$ initiates a restructuring; Payout$_{j,t+4}$, for whether firm $j$ increases payouts substantially; CEO$_{j,t+4}$, for whether firm $j$ changes CEO; Board$_{j,t+4}$, for whether firm $j$ changes board composition due to activism; and 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. Actions$_{j,t+4}$ is the sum of the five indicator variables. Independent variables are firm characteristics we describe in Appendix B. We present $t$-statistics calculated in a manner similar to Fama-MacBeth cross-sectional regressions in parenthesis. *** indicates significance at 1% level, ** indicates 5%, and * indicates 10%.

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Appendix D. Estimation and Identification

D.1. Likelihood function details

We compute the likelihood function for each observed campaign as:

$$L_c(\theta) = L_{gap}^c(\theta) \cdot L_{13-D}^c(\theta) \cdot L_{car}^c(\theta) \cdot L_{outcome}^c(\theta).$$  (35)

$L_{gap}^c(\theta)$ is the probability $A$ does not initiate another campaign until the date of their next observed campaign. Writing $t$ for the date of this campaign, and $d$ for the number of days until $A$’s next campaign occurs, we have:

$$L_{gap}^c(\theta) = \sum_{s=t+1}^{t+d-1} \left( 1 - \frac{\lambda_c}{365} \right) + \frac{\lambda_c}{365} (r_s(1 - d_{agr}(r_s)) + (1 - r_s)(1 - d_{caut}(r_s))).$$  (36)

where $r_s$ is $A$’s reputation on day $s$. If $c$ is $A$’s last campaign in our sample, we set $d$ equal to the smaller of 365 and the number of days until our sample ends on 12/31/2016.\footnote{This approach allows us to ignore any days before an activist’s first campaign, and limit the potential impact of long absences after an activist’s last campaign in our sample, perhaps because they exit activism altogether, to a maximum of 365 days.}

$L_{13-D}^c(\theta)$ is the probability $A$ receives a campaign opportunity and chooses 13-D on date $t$, given pre-campaign reputation $r_t$, which satisfies:

$$L_{13-D}^c(\theta) = \frac{\lambda_c}{365} (r_t d_{agr}(r_t) + (1 - r_t)d_{caut}(r_t)).$$  (37)

$L_{car}^c(\theta)$ is the probability of observed market returns CAR given pre-campaign reputation $r_t$ and $A$’s choice of 13-D:

$$L_{car}^c(\theta) = \phi \left( \frac{CAR - \mathbb{P}(\text{Settle or Fight}|r_t, 13-D)}{\sigma_{car}} \right),$$  (38)

$$\mathbb{P}(\text{Settle or Fight}|r_t, 13-D) = y(r_t) + (1 - y(r_t))p_f(r_t),$$  (39)

where $\phi$ is the PDF of the standard normal distribution.

Finally, $L_{outcome}^c(\theta)$ is the probability of observed outcome o given pre-campaign reputation $r_t$ and $A$’s choice of 13-D:

$$L_{outcome}^c(\theta) = \begin{cases} (1 - y(r_t))p_f(r_t) & \text{if } \text{Proxy} = 1 \\ y(r_t)\mathbb{P}(a|\text{Settle}) + (1 - y(r_t))(1 - p_f(r_t))\mathbb{P}(a|\text{Fold}) & \text{if } \text{Proxy} = 0 \end{cases}$$  (40)

D.2. Mapping between $\mu$ and zero-reputation probabilities

As described in Section 4.3, to ease the interpretation of our model’s parameters, we map means of log costs $\mu_L$, $\mu_M$, $\mu_{agr}$, and $\mu_{caut}$ to what they imply for strategies when reputation equals zero.
This mapping is:

\[
\begin{align*}
f_{\text{caut},0} &= \Phi \left( \tau_A (\log(\Delta) - \mu_{\text{caut}}) \right), \\
f_{\text{agr},0} &= \Phi \left( \tau_A (\log(\Delta) - \mu_{\text{agr}}) \right), \\
y_0 &= 1 - \Phi \left( \tau_M \left( \log \left( \frac{1 - f_{\text{caut},0}}{f_{\text{caut},0}} \right) - \mu_M \right) \right), \\
d_{\text{caut},0} &= \Phi \left( \tau_L (\log(T_{\text{caut},0}) - \mu_L) \right), \\
T_{\text{caut},0} &= y_0 \Delta + (1 - y_0) f_{\text{caut},0} \left( \Delta - \mathbb{E} \left[ \tilde{F}_A | \tilde{F}_A < \Delta, \mu_A = \mu_{\text{caut}} \right] \right).
\end{align*}
\]

\[\text{(41)-(45)}\]

D.3. Simulating samples

While our initial analysis focuses on the relation between estimated reputation and campaign outcomes in the observed sample, to assess how strategies and outcomes would change in counterfactual settings without reputation we need samples simulated from each model. For a given parameterization of the model \(\theta\), and given restrictions on the information set, we compute equilibrium strategies and reputation dynamics as described in Section 3.3 and Appendix A. With these in hand, we simulate samples using the following procedure:

1. Create a new activist \(A^{(i)}\) with initial type randomly assigned based on the unconditional probability \(r_0\), and birth date \(t_0\) randomly assigned within our sample period. We assume \(A^{(i)}\) receives a campaign opportunity on \(t_0\) and always chooses 13-D in this case.

2. Draw random type reset dates according to rate \(\lambda_r\), and at each date re-assign a new randomly drawn type, forming a complete path for the \(A^{(i)}\)’s true type.

3. Draw random campaign opportunity dates according to rate \(\lambda_c\).

4. Starting with the first campaign at \(t_0\), randomly draw costs \(\tilde{L}, \tilde{F}_M, \text{ and } \tilde{F}_A\) and compute the resulting campaign outcome. From this outcome, draw random \(a\) using Equation (19). Then compute post-campaign reputation \(r_{t+}\) and, based on Equation (22), pre-campaign reputation \(r_t\) for the next campaign opportunity.

5. Repeat Step 4 for all campaign opportunity dates drawn in Step 3.

6. Repeat Steps 1–5, creating new activists and recording the timing and outcome of their campaigns, until we have generated a sample matching the size of our empirical sample.

Based on the samples generated by this procedure, we compute moments for reputation, observed campaign outcomes, true campaign outcomes, each agent’s strategies, and payoffs for the activist and target shareholders.

D.4. 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:

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

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.

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

\[
LB_i = \inf \left\{ \theta_i \text{ s.t. } \Lambda(\{ \theta \text{ s.t. } \theta_i = \theta_i \}) \leq \chi^2(0.975, 1) \right\}, \\
UB_i = \sup \left\{ \theta_i \text{ s.t. } \Lambda(\{ \theta \text{ s.t. } \theta_i = \theta_i \}) \leq \chi^2(0.975, 1) \right\},
\]

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 typical maximum likelihood standard errors based on local estimates of the Hessian, these confidence intervals produce more-powerful tests and have the advantage of using information about the likelihood function’s shape away from our point estimates.

**D.5. Identification**

Like all maximum likelihood estimates, identifying our model requires that the likelihood function have a unique maximum at the true parameter values, and not be ‘too flat’ around this maximum. Our approach to confidence intervals is well-suited to showing this is indeed the case because it shows that forcing each individual parameter away from our point estimate results in significantly lower likelihood even when we allow other parameters to freely adjust. The relative tightness of the confidence intervals in Table 2 shows that our likelihood function is well-behaved in all dimensions and we have identification.

Aside from arguing our model is econometrically identified, we provide economic intuition for how we identify these parameters. To do so, Table D1 presents key moments in the data, values for these moments in our baseline model using estimated parameters, and values for these moments if we increase a single parameter to the upper bound of its confidence interval in Table 2 without changing any other model parameters. The twelve moments we present are the means of four outcome variables (13-D, AbActions, CAR, and Proxy) in the full sample and in subsamples containing campaigns in the bottom and top 10% of our baseline reputation measure.

Echoing the results in Table 4, we find our baseline model estimate fits the mean values of 13-D, CAR, and Proxy well, but underestimates the mean of AbActions. It also predicts cross-reputation differences very well for 13-D, slightly overstates differences in AbActions and CAR as a function of \( r_t \), and noticeably understates cross-campaign differences in Proxy.

The results in Table D1 also formalize the intuition provided in Section 4 for the economic sources of identification. Increasing \( \Delta, d_0, y_0, \) and \( f_{caut,0} \) directly increases the means of CAR, 13-D, AbActions, and Proxy, respectively. These four parameters can therefore loosely be interpreted as being identified by the means of these variables. Increasing \( f_{agr,0} \) has little impact on low \( r_t \) outcomes but a large impact on high \( r_t \) outcomes, meaning it is identified by the extent of aggression and success by the highest reputation activists.

Increasing \( \tau_L \) increases the spread in 13-D between low and high \( r_t \) campaigns. Similarly, increasing \( \tau_M \) increases the spread in AbActions and CAR between low and high \( r_t \) campaigns. Changes in all three \( \tau \) affect the spread in Proxy because we only observe a proxy fight when \( A \) chooses 13-D, \( M \) chooses Refuse, and \( A \) chooses Fight, meaning its probability is affected by costs at all three stages.\(^{23}\) Table D1 therefore shows the \( \tau \) are jointly identified by their differential effects

\(^{23}\)Note that with an increased \( \tau_M \), high \( r_t \) campaigns are settled so frequently they result in lower average Proxy despite the activist being more likely to fight if refused.
on the four different high vs. low reputation spreads, and more generally the shapes of the relations between \( r_t \) and outcome variables for \( r_t \) between zero and one.

Increasing initial reputation \( r_0 \) makes campaigns more frequent and successful across the board because there are more aggressive activists and reputation is therefore consistently higher. Increasing the type reset rate \( \lambda_r \) also increases the frequency and success of low reputation campaigns because they occur at slightly higher reputation due to mean reversion towards \( r_0 \). However, increasing \( \lambda_r \) has the opposite effect as increasing \( r_0 \) on high reputation activists because the mean reversion pulls their reputations downwards and dampens their success. We can therefore identify \( r_0 \) and \( \lambda_r \) jointly using the overall success and frequency of campaigns, most of which occur at low reputations, together with the overall success and frequency at high reputations.

Table D1: Identification

We present model predictions and observed outcomes averaged across different samples of campaigns for four different outcome variables. The first is 13-D, an indicator for whether there is a campaign initiation on a given activist-day. The second is AbActions, 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. The first row presents averages in the data. Each subsequent row represents a different parameterization for our model, starting with the baseline estimates we present in Table 2 and then increasing each parameter individually to the upper bound of the confidence interval in Table 2. For each parameterization, we compute average model predictions for the four outcome variables as a function of model-implied reputation, and compare this to average observed outcomes in the full sample (‘all’), among the bottom 10% of observations by \( r_t \) (‘Low \( r \)’) and among the top 10% of observations (‘Hi \( r \)’). 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.

<table>
<thead>
<tr>
<th>Sample:</th>
<th>13-D (× 365)</th>
<th>Ab Actions</th>
<th>CAR (%)</th>
<th>Proxy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All Low ( r ) Hi ( r )</td>
<td>All Low ( r ) Hi ( r )</td>
<td>All Low ( r ) Hi ( r )</td>
<td>All Low ( r ) Hi ( r )</td>
</tr>
<tr>
<td>Data</td>
<td>1.00 0.58 3.50</td>
<td>0.78 0.73 1.24</td>
<td>2.82 2.78 4.59</td>
<td>14.30 11.62 36.87</td>
</tr>
<tr>
<td>Baseline</td>
<td>0.93 0.62 3.48</td>
<td>0.65 0.52 1.08</td>
<td>2.80 2.25 4.61</td>
<td>13.74 10.12 25.55</td>
</tr>
<tr>
<td>( \Delta \uparrow )</td>
<td>0.84 0.57 3.33</td>
<td>0.65 0.52 1.07</td>
<td>4.21 3.34 6.92</td>
<td>13.65 9.86 25.37</td>
</tr>
<tr>
<td>( d_0 \uparrow )</td>
<td>3.71 3.23 7.72</td>
<td>0.54 0.50 0.90</td>
<td>2.32 2.16 3.85</td>
<td>10.63 9.58 20.61</td>
</tr>
<tr>
<td>( \tau_L \uparrow )</td>
<td>1.88 0.90 9.65</td>
<td>0.57 0.51 0.92</td>
<td>2.43 2.20 3.96</td>
<td>11.32 9.80 21.35</td>
</tr>
<tr>
<td>( y_0 \uparrow )</td>
<td>0.82 0.59 2.65</td>
<td>0.78 0.65 1.16</td>
<td>3.33 2.77 4.99</td>
<td>12.16 9.14 21.00</td>
</tr>
<tr>
<td>( \tau_M \uparrow )</td>
<td>2.20 1.20 7.33</td>
<td>0.82 0.66 1.51</td>
<td>3.52 2.81 6.48</td>
<td>7.30 8.50 0.66</td>
</tr>
<tr>
<td>( f_{0,caut} \uparrow )</td>
<td>0.77 0.56 2.29</td>
<td>0.72 0.62 1.01</td>
<td>3.11 2.65 4.34</td>
<td>20.54 16.96 29.88</td>
</tr>
<tr>
<td>( f_{0,agr} \uparrow )</td>
<td>1.00 0.63 4.26</td>
<td>0.66 0.53 1.19</td>
<td>2.83 2.28 5.11</td>
<td>13.84 10.31 28.00</td>
</tr>
<tr>
<td>( \tau_A \uparrow )</td>
<td>0.98 0.65 3.46</td>
<td>0.66 0.54 1.09</td>
<td>2.84 2.32 4.66</td>
<td>13.99 10.54 25.80</td>
</tr>
<tr>
<td>( r_0 \uparrow )</td>
<td>1.09 0.82 3.48</td>
<td>0.72 0.61 1.08</td>
<td>3.10 2.63 4.64</td>
<td>15.71 12.57 25.71</td>
</tr>
<tr>
<td>( \lambda_r \uparrow )</td>
<td>0.98 0.70 3.43</td>
<td>0.65 0.54 1.04</td>
<td>2.80 2.31 4.46</td>
<td>13.73 10.52 24.65</td>
</tr>
</tbody>
</table>
References


Figure 1: Estimated Equilibrium

We plot equilibrium properties of our model using estimated parameters. The first plot shows the probability the activist chooses $13-D$. The second shows the probability the target chooses $Settle$. The third shows the probability the activist chooses $Fight$. The fourth shows each type of activists’ value function. The fifth shows post-campaign reputation $r_{t+}$ conditional on each possible campaign outcome. All five plots are a function of pre-campaign reputation $r_t$. 

![Equilibrium Properties Diagram](image-url)
Figure 1 (cont’d): Estimated Equilibrium

- \( P(\text{Fight} | \text{Refuse}) \)

- Value function

- Post-campaign reputation \( r_{t+} \)

Legend:
- \( f_{\text{out}} \) (static)
- \( f_{\text{agr}} \) (static)
- \( f_{\text{out}} \) (dynamic)
- \( f_{\text{agr}} \) (dynamic)

Legend for value function:
- \( V_{\text{out}} \)
- \( V_{\text{agr}} \)

Legend for post-campaign reputation:
- \( \text{Fight} \)
- \( \text{Settle} \)
- \( \text{Fold} \)
Figure 2: Example Reputation Dynamics

We plot the time series of reputations for four activists in our sample, Icahn Enterprises, Starboard Value, Loeb Partners, and Riley Investment Management, based on the sample of their campaigns and our estimated model. Each plot shows reputation between campaigns as a line, and marks campaign dates with a circle if they do not feature a proxy fight and an x if they do. For campaigns without a proxy fight, the darkness of the circle is proportional to the probability the campaign was settled based on observed target actions and our estimated model.
Figure 2: Example Reputation Dynamics (cont’d)

Loeb Partners’ Reputation $r_t$

- Fight
- Settle
- Fold

Riley Investment Management’s Reputation $r_t$

- Fight
- Settle
- Fold


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.
Table 1: Descriptive Statistics

We present summary statistics for the activist campaigns in our sample. Proxy is an indicator for whether the campaign features a proxy fight. CAR is the target’s [-1,1] market-adjusted return around the campaign initiation date. 13-D is an indicator for whether there is a campaign initiation on a given activist-day. The five indicator variables for target actions in the year following campaign initiation are: Reorg, for whether the target initiates a restructuring; Payout, for whether the target substantially increases payouts to shareholders; CEO, for whether the target changes CEO; Board, for whether the target changes board composition due to activism; and Acq, for whether the target engages in a merger or acquisition. For each action indicator, \( \hat{\text{Action}} \) is its expected value in the absence of activism based on the regressions discussed in Appendix C and \( \text{Ab\ Action} \) is \( \text{Action} - \hat{\text{Action}} \). Actions is the sum of these five indicators, \( \hat{\text{Actions}} \) is the sum of the \( \hat{\text{Action}} \)s, and \( \text{Ab\ Actions} \) is the difference between the two. We present averages for each variable in the full sample and in subsamples sorted by whether Proxy = 1 and whether it is the activist’s first campaign. 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.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std</th>
<th>Proxy = 1 N = 348</th>
<th>Proxy = 0 N = 2086</th>
<th>First camp. N = 419</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proxy (%)</td>
<td>14.3</td>
<td>35.0</td>
<td>100.0</td>
<td>0.0</td>
<td>13.8</td>
</tr>
<tr>
<td>CAR (%)</td>
<td>2.8</td>
<td>9.0</td>
<td>3.8</td>
<td>2.7</td>
<td>1.9</td>
</tr>
<tr>
<td>13-D (× 365)</td>
<td>1.0</td>
<td>19.1</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Reorg (%)</td>
<td>32.6</td>
<td>46.9</td>
<td>48.3</td>
<td>30.0</td>
<td>30.1</td>
</tr>
<tr>
<td>( \hat{\text{Reorg}} ) (%)</td>
<td>13.9</td>
<td>9.4</td>
<td>16.0</td>
<td>13.5</td>
<td>12.5</td>
</tr>
<tr>
<td>( \text{Ab\ Reorg} ) (%)</td>
<td>18.7</td>
<td>45.6</td>
<td>32.3</td>
<td>16.5</td>
<td>17.6</td>
</tr>
<tr>
<td>Payout (%)</td>
<td>14.7</td>
<td>35.4</td>
<td>16.7</td>
<td>14.4</td>
<td>12.6</td>
</tr>
<tr>
<td>( \hat{\text{Payout}} ) (%)</td>
<td>10.1</td>
<td>14.6</td>
<td>10.5</td>
<td>10.1</td>
<td>8.6</td>
</tr>
<tr>
<td>( \text{Ab\ Payout} ) (%)</td>
<td>4.6</td>
<td>32.5</td>
<td>6.2</td>
<td>4.3</td>
<td>4.0</td>
</tr>
<tr>
<td>CEO (%)</td>
<td>25.4</td>
<td>43.6</td>
<td>31.6</td>
<td>24.4</td>
<td>24.3</td>
</tr>
<tr>
<td>( \hat{\text{CEO}} ) (%)</td>
<td>13.7</td>
<td>4.0</td>
<td>14.1</td>
<td>13.6</td>
<td>13.0</td>
</tr>
<tr>
<td>( \text{Ab\ CEO} ) (%)</td>
<td>11.7</td>
<td>43.6</td>
<td>17.5</td>
<td>10.8</td>
<td>11.4</td>
</tr>
<tr>
<td>Board (%)</td>
<td>25.6</td>
<td>43.6</td>
<td>68.1</td>
<td>18.5</td>
<td>27.0</td>
</tr>
<tr>
<td>( \hat{\text{Board}} ) (%)</td>
<td>0.4</td>
<td>0.4</td>
<td>0.5</td>
<td>0.4</td>
<td>0.3</td>
</tr>
<tr>
<td>( \text{Ab\ Board} ) (%)</td>
<td>25.2</td>
<td>43.6</td>
<td>67.6</td>
<td>18.1</td>
<td>26.6</td>
</tr>
<tr>
<td>Acq (%)</td>
<td>27.8</td>
<td>44.8</td>
<td>42.0</td>
<td>25.4</td>
<td>28.6</td>
</tr>
<tr>
<td>( \hat{\text{Acq}} ) (%)</td>
<td>10.3</td>
<td>4.1</td>
<td>11.2</td>
<td>10.1</td>
<td>9.5</td>
</tr>
<tr>
<td>( \text{Ab\ Acq} ) (%)</td>
<td>17.5</td>
<td>44.6</td>
<td>30.8</td>
<td>15.3</td>
<td>19.2</td>
</tr>
<tr>
<td>Actions (×100)</td>
<td>126.1</td>
<td>123.4</td>
<td>206.6</td>
<td>112.7</td>
<td>122.7</td>
</tr>
<tr>
<td>( \hat{\text{Actions}} ) (×100)</td>
<td>48.4</td>
<td>22.8</td>
<td>52.3</td>
<td>47.7</td>
<td>43.9</td>
</tr>
<tr>
<td>( \text{Ab\ Actions} ) (×100)</td>
<td>77.7</td>
<td>120.1</td>
<td>154.3</td>
<td>64.9</td>
<td>78.8</td>
</tr>
</tbody>
</table>
Table 2: Estimated Model Parameters and Hypothesis Tests

Panel A describes the model parameters we estimate and gives their estimated values and 95% confidence intervals based on the likelihood ratio approach we describe in Appendix D. Panel B describes the model parameters we calibrate and gives their values. Panel C presents results from testing the no reputation and full information hypotheses. For both, we present re-estimated model parameters as well as the Wilks (1938) likelihood ratio $\chi^2$ statistic and its $p$-value. Our sample consists of 2,434 campaigns initiated by hedge funds during 1999–2016.

### Panel A: Estimated parameters

<table>
<thead>
<tr>
<th>Param.</th>
<th>Description</th>
<th>Estimate</th>
<th>95% C.I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta$</td>
<td>Value of project A demands / market cap (%)</td>
<td>6.62</td>
<td>[5.70, 7.35]</td>
</tr>
<tr>
<td>$d_{h,0}$</td>
<td>Prob. cautious A chooses 13-D given $r_{t-} = 0$ (%)</td>
<td>4.16</td>
<td>[2.78, 8.83]</td>
</tr>
<tr>
<td>$\tau_L$</td>
<td>Precision log(Cost of campaign to A)</td>
<td>1.65</td>
<td>[0.48, 2.06]</td>
</tr>
<tr>
<td>$y_0$</td>
<td>Prob. M settles given $r_{t-} = 0$ (%)</td>
<td>21.82</td>
<td>[12.87, 24.22]</td>
</tr>
<tr>
<td>$\tau_A$</td>
<td>Precision log($M$ proxy fight cost/$M$ project cost)</td>
<td>0.33</td>
<td>[0.11, 0.48]</td>
</tr>
<tr>
<td>$f_{caut,0}$</td>
<td>Prob cautious A chooses fight given $r_{t-} = 0$ (%)</td>
<td>11.10</td>
<td>[4.44, 14.66]</td>
</tr>
<tr>
<td>$f_{agr,0}$</td>
<td>Prob aggressive A chooses fight given $r_{t-} = 0$ (%)</td>
<td>48.03</td>
<td>[40.73, 60.38]</td>
</tr>
<tr>
<td>$\tau_F$</td>
<td>Precision log($A$ proxy fight cost)</td>
<td>1.45</td>
<td>[0.72, 2.42]</td>
</tr>
<tr>
<td>$r_0$</td>
<td>Unconditional prob. A is aggressive (%)</td>
<td>2.05</td>
<td>[1.00, 9.80]</td>
</tr>
<tr>
<td>$\lambda_r$</td>
<td>Arrival rate of type resets (annualized)</td>
<td>0.19</td>
<td>[0.08, 0.36]</td>
</tr>
</tbody>
</table>

### Panel B: Calibrated parameters

<table>
<thead>
<tr>
<th>Param.</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>Activists’ annual discount factor</td>
<td>0.90</td>
</tr>
<tr>
<td>$\sigma_{car}$</td>
<td>Standard dev. of camp. announcement 3-day CAR (%)</td>
<td>8.99</td>
</tr>
<tr>
<td>$\beta_{reorg}$</td>
<td>Added prob. of reorganization in successful camp. (%)</td>
<td>32.25</td>
</tr>
<tr>
<td>$\beta_{payout}$</td>
<td>Added prob. of payout increase in successful camp. (%)</td>
<td>6.16</td>
</tr>
<tr>
<td>$\beta_{ceo}$</td>
<td>Added prob. of CEO change in successful camp. (%)</td>
<td>17.53</td>
</tr>
<tr>
<td>$\beta_{board}$</td>
<td>Added prob. of board change in successful camp. (%)</td>
<td>67.63</td>
</tr>
<tr>
<td>$\beta_{acq}$</td>
<td>Added prob. of M&amp;A activity in successful camp. (%)</td>
<td>30.76</td>
</tr>
<tr>
<td>$\lambda_c$</td>
<td>Arrival rate of camp. opportunities (annualized)</td>
<td>10.00</td>
</tr>
</tbody>
</table>

### Panel C: Hypothesis tests

<table>
<thead>
<tr>
<th>Model</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>$f_{agr,0}$</th>
<th>$\tau_A$</th>
<th>$r_0$</th>
<th>$\lambda_r$</th>
<th>$\chi^2$</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</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>
<td></td>
<td></td>
</tr>
<tr>
<td>No reputation</td>
<td>6.67</td>
<td>9.94</td>
<td>-</td>
<td>28.05</td>
<td>-</td>
<td>19.87</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>340.1</td>
<td>0.00%</td>
</tr>
<tr>
<td>Full information</td>
<td>6.80</td>
<td>9.12</td>
<td>2.00</td>
<td>29.52</td>
<td>0.12</td>
<td>12.36</td>
<td>64.15</td>
<td>-</td>
<td>0.85</td>
<td>-</td>
<td>21.0</td>
<td>0.00%</td>
</tr>
</tbody>
</table>
Table 3: Reputation Summary Statistics

In Panel A we present summary statistics for estimated post- and pre-campaign activist reputation measures $r_{t+}$ and $r_t$, which we describe in Section 4.3. In Panel B we list the 25 activists with the highest average $r_t$. *Ab Actions* is the total number of abnormal activism-related corporate actions by target firms in the year following campaign initiation. *CAR* is the target’s [-1,1] market-adjusted return around the campaign initiation date. Our sample consists of 2,434 campaigns initiated by hedge funds during 1999–2016.

**Panel A: Distribution of reputation across campaigns**

<table>
<thead>
<tr>
<th>Percentile</th>
<th>Mean</th>
<th>Variance</th>
<th>1st</th>
<th>5th</th>
<th>10th</th>
<th>25th</th>
<th>50th</th>
<th>75th</th>
<th>90th</th>
<th>95th</th>
<th>99th</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_{t+}$</td>
<td>14.35</td>
<td>25.31</td>
<td>0.36</td>
<td>0.39</td>
<td>0.47</td>
<td>1.01</td>
<td>2.32</td>
<td>12.16</td>
<td>55.69</td>
<td>87.44</td>
<td>98.01</td>
</tr>
<tr>
<td>$r_t$</td>
<td>10.81</td>
<td>23.01</td>
<td>0.10</td>
<td>0.10</td>
<td>0.28</td>
<td>0.55</td>
<td>7.25</td>
<td>41.87</td>
<td>77.96</td>
<td>94.57</td>
<td></td>
</tr>
</tbody>
</table>

**Panel B: Highest reputation activists**

<table>
<thead>
<tr>
<th>Activist</th>
<th>Mean $r_t$</th>
<th>Number of Campaigns</th>
<th>Number of Proxy Fights</th>
<th>Mean <em>Ab Actions</em></th>
<th>Mean <em>CAR</em></th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Starboard Value</td>
<td>79.15</td>
<td>77</td>
<td>30</td>
<td>2.25</td>
<td>4.65%</td>
</tr>
<tr>
<td>2 Icahn Enterprises</td>
<td>61.70</td>
<td>77</td>
<td>28</td>
<td>1.84</td>
<td>6.21%</td>
</tr>
<tr>
<td>3 Lone Star Value Mgmt</td>
<td>47.36</td>
<td>16</td>
<td>8</td>
<td>0.88</td>
<td>4.27%</td>
</tr>
<tr>
<td>4 Clinton Group</td>
<td>44.07</td>
<td>29</td>
<td>12</td>
<td>1.62</td>
<td>5.13%</td>
</tr>
<tr>
<td>5 Riley Inv Mgmt</td>
<td>42.79</td>
<td>24</td>
<td>7</td>
<td>1.75</td>
<td>3.02%</td>
</tr>
<tr>
<td>6 Vertex Capital Adv</td>
<td>28.26</td>
<td>11</td>
<td>3</td>
<td>1.55</td>
<td>1.50%</td>
</tr>
<tr>
<td>7 Steel Ptrs</td>
<td>27.93</td>
<td>56</td>
<td>9</td>
<td>1.32</td>
<td>2.55%</td>
</tr>
<tr>
<td>8 Pirate Capital</td>
<td>27.85</td>
<td>18</td>
<td>3</td>
<td>1.78</td>
<td>2.84%</td>
</tr>
<tr>
<td>9 Engaged Capital</td>
<td>26.18</td>
<td>12</td>
<td>4</td>
<td>1.92</td>
<td>2.57%</td>
</tr>
<tr>
<td>10 Newcastle Ptrs L P</td>
<td>24.51</td>
<td>16</td>
<td>9</td>
<td>1.56</td>
<td>8.92%</td>
</tr>
<tr>
<td>11 Bulldog Inv</td>
<td>24.15</td>
<td>24</td>
<td>12</td>
<td>1.13</td>
<td>0.41%</td>
</tr>
<tr>
<td>12 Voce Capital Mgmt</td>
<td>23.89</td>
<td>10</td>
<td>6</td>
<td>2.40</td>
<td>5.84%</td>
</tr>
<tr>
<td>13 Lawrence Seidman</td>
<td>21.46</td>
<td>34</td>
<td>12</td>
<td>1.09</td>
<td>4.54%</td>
</tr>
<tr>
<td>14 Barington Companies</td>
<td>19.32</td>
<td>28</td>
<td>10</td>
<td>1.71</td>
<td>4.09%</td>
</tr>
<tr>
<td>15 Land &amp; Buildings</td>
<td>17.65</td>
<td>6</td>
<td>4</td>
<td>1.83</td>
<td>5.63%</td>
</tr>
<tr>
<td>16 Harbinger Capital Ptrs</td>
<td>16.64</td>
<td>16</td>
<td>4</td>
<td>2.25</td>
<td>0.25%</td>
</tr>
<tr>
<td>17 PL Capital</td>
<td>16.37</td>
<td>39</td>
<td>10</td>
<td>0.79</td>
<td>3.27%</td>
</tr>
<tr>
<td>18 Shamrock Ptrs</td>
<td>15.53</td>
<td>19</td>
<td>3</td>
<td>1.63</td>
<td>0.22%</td>
</tr>
<tr>
<td>19 Millennium Mgmt</td>
<td>14.69</td>
<td>44</td>
<td>0</td>
<td>0.82</td>
<td>−0.30%</td>
</tr>
<tr>
<td>20 Sandell Asset Mgmt</td>
<td>14.38</td>
<td>15</td>
<td>8</td>
<td>2.20</td>
<td>2.19%</td>
</tr>
<tr>
<td>21 ValueAct Capital Mgmt</td>
<td>14.28</td>
<td>80</td>
<td>1</td>
<td>1.48</td>
<td>1.80%</td>
</tr>
<tr>
<td>22 Elliott Associates</td>
<td>13.16</td>
<td>45</td>
<td>5</td>
<td>1.84</td>
<td>4.60%</td>
</tr>
<tr>
<td>23 Third Point</td>
<td>11.87</td>
<td>36</td>
<td>5</td>
<td>1.67</td>
<td>3.44%</td>
</tr>
<tr>
<td>24 Stilwell Joseph</td>
<td>9.95</td>
<td>28</td>
<td>9</td>
<td>0.93</td>
<td>1.76%</td>
</tr>
<tr>
<td>25 Tontine Assoc.</td>
<td>8.79</td>
<td>60</td>
<td>0</td>
<td>0.57</td>
<td>2.76%</td>
</tr>
</tbody>
</table>
Table 4: Equilibrium Effects of Reputation

We present average strategies, outcomes, and motivations based on our estimated model in the full sample and subsamples by reputation. Strategies are described by $d_{caut}$ and $d_{agr}$, cautious and aggressive activist’s probability of choosing 13-D; $y$, the target’s probability of settling; and $f_{caut}$ and $f_{agr}$, cautious and aggressive activist’s probability of fighting. 13-D, Ab Actions, CAR, and Proxy are defined in Table 1. ‘Short-term profitable’ is the fraction of campaign initiations or proxy fights which have positive expected profits in the current campaign, with the remainder being ‘Reputation building.’ Our sample for Panel A is 737,004 activist-days during 1999–2016. Our sample for Panel B is 2,434 campaigns initiated by hedge funds during 1999–2016.

### Panel A: Activist-days sorted by $r_t$

<table>
<thead>
<tr>
<th>$r_t$ (%) range:</th>
<th>All</th>
<th>[0, 0.5]</th>
<th>[0.5, 5]</th>
<th>[5, 50]</th>
<th>[50, 100]</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of activst-days</td>
<td>100.00</td>
<td>65.85</td>
<td>23.11</td>
<td>7.96</td>
<td>3.07</td>
</tr>
<tr>
<td><strong>Strategies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$d_{caut}$ (% of opportunities)</td>
<td>8.74</td>
<td>6.10</td>
<td>9.88</td>
<td>20.04</td>
<td>27.60</td>
</tr>
<tr>
<td>$d_{agr}$ (% of opportunities)</td>
<td>39.57</td>
<td>40.35</td>
<td>37.84</td>
<td>38.97</td>
<td>37.36</td>
</tr>
<tr>
<td><strong>Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13-D (model) ($\times 365$)</td>
<td>1.00</td>
<td>0.58</td>
<td>1.17</td>
<td>2.99</td>
<td>3.50</td>
</tr>
<tr>
<td>13-D (data) ($\times 365$)</td>
<td>0.93</td>
<td>0.62</td>
<td>1.03</td>
<td>2.29</td>
<td>3.48</td>
</tr>
<tr>
<td><strong>Motivations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short-term profitable (% of 13-D)</td>
<td>80.08</td>
<td>84.75</td>
<td>73.20</td>
<td>71.77</td>
<td>91.82</td>
</tr>
<tr>
<td>Reputation building (% of 13-D)</td>
<td>19.92</td>
<td>15.25</td>
<td>26.80</td>
<td>28.23</td>
<td>8.18</td>
</tr>
</tbody>
</table>

### Panel B: Campaigns sorted by $r_t$

<table>
<thead>
<tr>
<th>$r_t$ (%) range:</th>
<th>All</th>
<th>[0, 0.5]</th>
<th>[0.5, 5]</th>
<th>[5, 50]</th>
<th>[50, 100]</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of campaigns</td>
<td>100.00</td>
<td>48.81</td>
<td>22.51</td>
<td>19.76</td>
<td>8.92</td>
</tr>
<tr>
<td><strong>Strategies</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$y$ (% of 13-D)</td>
<td>28.55</td>
<td>23.86</td>
<td>26.97</td>
<td>34.89</td>
<td>44.11</td>
</tr>
<tr>
<td>$f_{caut}$ (% of Refuse)</td>
<td>14.62</td>
<td>12.61</td>
<td>14.54</td>
<td>18.41</td>
<td>17.45</td>
</tr>
<tr>
<td>$f_{agr}$ (% of Refuse)</td>
<td>58.98</td>
<td>59.26</td>
<td>60.19</td>
<td>60.07</td>
<td>51.96</td>
</tr>
<tr>
<td><strong>Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ab Actions (model)</td>
<td>0.65</td>
<td>0.52</td>
<td>0.61</td>
<td>0.83</td>
<td>1.08</td>
</tr>
<tr>
<td>Ab Actions (data)</td>
<td>0.78</td>
<td>0.73</td>
<td>0.69</td>
<td>0.77</td>
<td>1.24</td>
</tr>
<tr>
<td>Ab Actions</td>
<td>Proxy = 0 (model)</td>
<td>0.51</td>
<td>0.41</td>
<td>0.48</td>
<td>0.66</td>
</tr>
<tr>
<td>Ab Actions</td>
<td>Proxy = 0 (data)</td>
<td>0.65</td>
<td>0.63</td>
<td>0.58</td>
<td>0.66</td>
</tr>
<tr>
<td>CAR (model) (%)</td>
<td>2.80</td>
<td>2.25</td>
<td>2.61</td>
<td>3.55</td>
<td>4.61</td>
</tr>
<tr>
<td>CAR (data) (%)</td>
<td>2.82</td>
<td>2.78</td>
<td>2.53</td>
<td>2.45</td>
<td>4.59</td>
</tr>
<tr>
<td>Proxy (model) (%)</td>
<td>13.74</td>
<td>10.12</td>
<td>12.46</td>
<td>18.79</td>
<td>25.55</td>
</tr>
<tr>
<td>Proxy (data) (%)</td>
<td>14.30</td>
<td>11.62</td>
<td>10.22</td>
<td>15.38</td>
<td>36.87</td>
</tr>
<tr>
<td><strong>Motivations</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Short-term profitable (% of Fight)</td>
<td>81.17</td>
<td>87.95</td>
<td>76.62</td>
<td>68.77</td>
<td>90.16</td>
</tr>
<tr>
<td>Reputation building (% of Fight)</td>
<td>18.83</td>
<td>12.05</td>
<td>23.38</td>
<td>31.23</td>
<td>9.84</td>
</tr>
</tbody>
</table>
Table 5: Reputation and Activist Campaign Outcomes

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. 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%.

<table>
<thead>
<tr>
<th></th>
<th>13-D</th>
<th>( Ab\ Actions )</th>
<th>( Ab\ Actions )</th>
<th>( CAR )</th>
<th>Proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Main regressions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Predicted Coefficient</td>
<td>4.17</td>
<td>0.70</td>
<td>0.67</td>
<td>3.02</td>
<td>19.77</td>
</tr>
<tr>
<td>( r_t )</td>
<td>4.28***</td>
<td>0.71***</td>
<td>0.55**</td>
<td>2.53***</td>
<td>34.08***</td>
</tr>
<tr>
<td></td>
<td>(0.55)</td>
<td>(0.17)</td>
<td>(0.17)</td>
<td>(0.73)</td>
<td>(4.08)</td>
</tr>
<tr>
<td>Obs</td>
<td>736,959</td>
<td>2,434</td>
<td>2,086</td>
<td>2,434</td>
<td>2,434</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.00</td>
<td>0.06</td>
<td>0.06</td>
<td>0.02</td>
<td>0.05</td>
</tr>
<tr>
<td>Sample</td>
<td>Daily Panel</td>
<td>All Camp.</td>
<td>Proxy= 0</td>
<td>All Camp.</td>
<td>All Camp.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>13-D</th>
<th>( Ab\ Actions )</th>
<th>( Ab\ Actions )</th>
<th>( CAR )</th>
<th>Proxy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel B: Robustness</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( r_t )</td>
<td>2.30***</td>
<td>0.82***</td>
<td>0.61***</td>
<td>2.98***</td>
<td>42.97***</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td>(0.19)</td>
<td>(0.20)</td>
<td>(0.99)</td>
<td>(6.36)</td>
</tr>
<tr>
<td>( \log ) Portfolio Size</td>
<td>0.02</td>
<td>0.01</td>
<td>0.01</td>
<td>0.06</td>
<td>-2.44***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.16)</td>
<td>(0.67)</td>
</tr>
<tr>
<td>( Portfolio\ Turnover )</td>
<td>-0.17**</td>
<td>-0.09</td>
<td>-0.05</td>
<td>0.06</td>
<td>-0.61</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.49)</td>
<td>(1.88)</td>
</tr>
<tr>
<td>( Prior\ Campaigns )</td>
<td>0.05***</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.22***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>( Stake Size )</td>
<td>-0.58</td>
<td>-0.02</td>
<td>0.69</td>
<td>-44.28***</td>
<td>(16.58)</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.54)</td>
<td>(3.93)</td>
<td>(16.58)</td>
<td></td>
</tr>
<tr>
<td>( Top\ HF )</td>
<td>0.03</td>
<td>0.09</td>
<td>0.14</td>
<td>-0.16</td>
<td>3.25</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.64)</td>
<td>(2.19)</td>
</tr>
<tr>
<td>Obs</td>
<td>736,959</td>
<td>2,434</td>
<td>2,086</td>
<td>2,434</td>
<td>2,434</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.002</td>
<td>0.055</td>
<td>0.052</td>
<td>0.021</td>
<td>0.050</td>
</tr>
<tr>
<td>Sample</td>
<td>Daily Panel</td>
<td>All Camp.</td>
<td>Proxy= 0</td>
<td>All Camp.</td>
<td>All Camp.</td>
</tr>
</tbody>
</table>
Table 6: Counterfactuals

This table presents average pre-opportunity reputation $r_t$, equilibrium strategies, and payoffs for target shareholders and activists in our baseline model and three counterfactuals. In the ‘no reputation’ counterfactual, targets do not consider the activist’s past campaigns when deciding whether to Settle. In the ‘no aggressive A’ counterfactual, there are no aggressive type activists. In the ‘full information’ counterfactual, activists’ types are common knowledge. For our baseline model and each counterfactual, we simulate 1000 samples and compute average reputation prior to each campaign opportunity, equilibrium strategies, and payoffs to target shareholders and activists across all campaigns in the simulated samples.

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Baseline</th>
<th>No reputation</th>
<th>No aggressive A</th>
<th>Full information</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Pre-opportunity reputation r_t$ (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cautious A</td>
<td>1.21</td>
<td>2.05</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Aggressive A</td>
<td>40.29</td>
<td>2.05</td>
<td>–</td>
<td>100.00</td>
</tr>
<tr>
<td>All</td>
<td>2.00</td>
<td>2.05</td>
<td>0.00</td>
<td>2.05</td>
</tr>
<tr>
<td>$13-D$ (% of opportunities)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cautious A</td>
<td>8.73</td>
<td>5.43</td>
<td>4.16</td>
<td>4.16</td>
</tr>
<tr>
<td>Aggressive A</td>
<td>38.62</td>
<td>15.82</td>
<td>–</td>
<td>35.89</td>
</tr>
<tr>
<td>All</td>
<td>9.34</td>
<td>5.65</td>
<td>4.16</td>
<td>4.81</td>
</tr>
<tr>
<td>$Settle$ (% of campaigns)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cautious A</td>
<td>26.50</td>
<td>23.81</td>
<td>21.82</td>
<td>21.82</td>
</tr>
<tr>
<td>Aggressive A</td>
<td>37.65</td>
<td>23.81</td>
<td>–</td>
<td>45.31</td>
</tr>
<tr>
<td>All</td>
<td>27.44</td>
<td>23.81</td>
<td>21.82</td>
<td>22.31</td>
</tr>
<tr>
<td>$Fight$ (% of refusals)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cautious A</td>
<td>13.82</td>
<td>11.10</td>
<td>11.10</td>
<td>11.10</td>
</tr>
<tr>
<td>Aggressive A</td>
<td>55.74</td>
<td>48.03</td>
<td>–</td>
<td>48.03</td>
</tr>
<tr>
<td>All</td>
<td>16.85</td>
<td>11.86</td>
<td>11.10</td>
<td>11.86</td>
</tr>
<tr>
<td>$Target shareholders’ average payoff (bp per opportunity)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cautious A</td>
<td>21.19</td>
<td>11.60</td>
<td>8.41</td>
<td>8.41</td>
</tr>
<tr>
<td>Aggressive A</td>
<td>185.11</td>
<td>63.28</td>
<td>–</td>
<td>170.05</td>
</tr>
<tr>
<td>All</td>
<td>24.53</td>
<td>12.67</td>
<td>8.41</td>
<td>11.73</td>
</tr>
<tr>
<td>$Activists’ average net payoff (bp per opportunity)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cautious A</td>
<td>2.62</td>
<td>1.94</td>
<td>1.33</td>
<td>1.33</td>
</tr>
<tr>
<td>Aggressive A</td>
<td>23.26</td>
<td>9.71</td>
<td>–</td>
<td>39.87</td>
</tr>
<tr>
<td>All</td>
<td>3.04</td>
<td>2.10</td>
<td>1.33</td>
<td>2.12</td>
</tr>
</tbody>
</table>
Table 7: 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>
</thead>
<tbody>
<tr>
<td>Campaigns</td>
<td>2434</td>
<td>1801</td>
<td>345</td>
<td>38</td>
<td>122</td>
<td>111</td>
<td>105</td>
</tr>
<tr>
<td>Activists</td>
<td>420</td>
<td>603</td>
<td>1</td>
<td>10</td>
<td>11</td>
<td>19</td>
<td>15</td>
</tr>
<tr>
<td>Mean(13-D) ( \times 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>
</tr>
<tr>
<td>Median ( r_t ) (%)</td>
<td>0.55</td>
<td>0.40</td>
<td>21.46</td>
<td>0.39</td>
<td>0.40</td>
<td>0.34</td>
<td>1.39</td>
</tr>
<tr>
<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>
</tr>
</tbody>
</table>

Panel B: Non hedge fund parameter estimates

<table>
<thead>
<tr>
<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_{agr,0} )</th>
<th>( \tau_A )</th>
<th>( \tau_0 )</th>
<th>( \lambda_r )</th>
</tr>
</thead>
<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>
<td>0.24</td>
<td>0.18</td>
<td>0.25</td>
</tr>
</tbody>
</table>

Panel C. Comparing moments and equilibrium properties

<table>
<thead>
<tr>
<th></th>
<th>Hedge Funds</th>
<th>All Non HF</th>
</tr>
</thead>
<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>
</tr>
</tbody>
</table>