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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 (see, e.g., Brav et al. (2008); Brav et al. (2010); and Bebchuk et al. (2019)). 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 quantify 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.

Activists in our model engage 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 buying shares in the target, the effort and expense related to communications with targets 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 value for shareholders but negative net value for them due to 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 only paying 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, "aggressive" types with lower average costs of proxy fights and "cautious" types with higher 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. 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." – *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 which 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 likelihood of 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 reorganizations, payout increases, CEO changes, board changes, and mergers observed in Compustat and Capital IQ.[1] These data allow us to identify model parameters using maximum likelihood based on the functional form of relations between activists' past and future and campaign frequency and outcomes.[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

[1]Unfortunately, as we discuss in Section 4.1, SharkWatch and other data providers have no comprehensive classification for whether a campaign was settled, forcing empirical research on settlements (e.g. in Bebchuk et al. (2019)) to estimate whether a specific campaign was settled using data from multiple sources.

[2]Our estimated reputation measure and main outcome variables for campaigns in our sample are available on the author's website.

per year, compared to only 0.6 for low reputation activists.[3] Moreover, 20% of campaigns 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 reject this "full information" version of our model using a likelihood ratio test. While our reputation model and the full-information alternative fit the data similarly well along many dimensions, our reputation model better fits the relations between within-activist changes in reputation and within-activist changes in the frequency and outcomes of their campaigns, both of which are significantly larger in the data than the full-information alternative predicts.

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

[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%.

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. Finally, we show that within-activist variation in reputation predicts within-activist differences in campaign frequency and target actions more-positively than is predicted by the no-reputation and full-information null hypotheses. Within-activist relations between reputation and target actions in non-proxy campaigns, target announcement returns, and proxy fights are too noisy to reject either our reputation model or the alternative models at the 5% level.

Our reduced-form tests also 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 measures of experience and reputation adapted from Boyson et al. (2016) and Krishnan et al. (2016), respectively.

2. Related literature

We add a unique perspective to the theoretical literature on investor activism by studying multiple sequential campaigns with asymmetric information about activists' cost of fighting. The existing literature focuses on a large shareholder of a single firm (examples include Burkart et al. (1997), Maug (1998), Aghion et al. (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. Levit (2018) 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 et al. (2010) and Denes et al. (2017), by using a structural approach to study reputation for proxy fighting.[4] Two related papers, Krishnan et al. (2016) and Boyson et al. (2016), examine activist hedge fund reputation and experience empirically. Krishnan et al. (2016) finds that short-term stock returns and long-term firm performance are both stronger following interventions by hedge funds with higher dollar values of recent activist positions. Boyson et al. (2016) shows activists with more experience produce larger announcement returns and better long-term target performance.

Bebchuk et al. (2019) finds that settlements often consist of board seats rather than direct corporate policy changes, can be formal legal contracts but are often informal understandings, and are related to activists' ability to credibly threaten a proxy fight. We formally model this credibility as arising in a dynamic reputation model, assess its impact using a structural estimation, and use activist-friendly actions to capture both formal and informal settlements.

[4] More-recent work shows activism is effective internationally (Becht et al. (2017)); is facilitated by passive investors (Appel et al. (2018)); improves targets' productive efficiency (Brav et al. (2015)), governance (Gantchev et al. (2019)), and innovation (Brav et al. (2018); and increases the likelihood of mergers (Boyson et al. (2017)).

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, allowing us to quantify dynamic reputation effects.

Our methodology is similar to other structural estimation papers in corporate finance, which use the variety of procedures summarized in Strebulaev and Whited (2012). Simulated method of moments (SMM) is the most common, employed recently in Nikolov and Whited (2014), Dimopoulos and Sacchetto (2014), Schroth et al. (2014), Warusawitharana (2015), and Glover (2016), among others. As discussed in Section 4, we use a maximum likelihood estimation (MLE), which is similar to the simulated maximum likelihood approach in Morellec et al. (2012). Compared to SMM, MLE has the advantage of using the full functional form of relations in the model for identification, avoiding subjective choices of moments and making it efficient from a statistical perspective. SMM, on the other hand, has the advantages of not forcing the model to fit every moment and not requiring a closed form solution for the likelihood function. We use MLE because we have a closed form solution and a rich enough model to fit the distribution of observed data in our setting.

3. Model

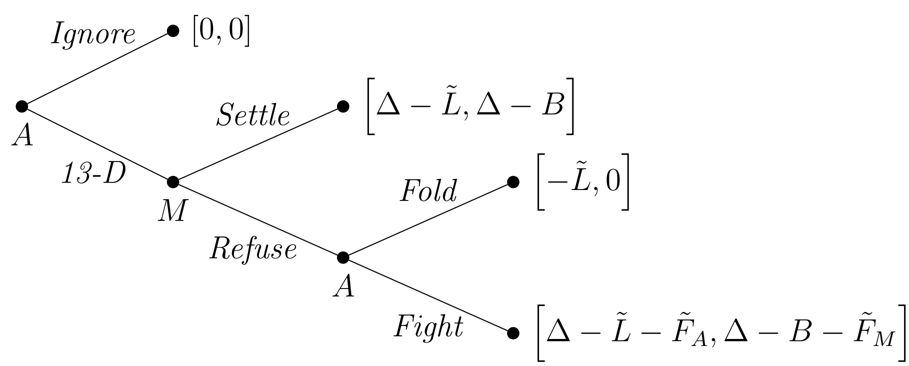
Our model adapts the canonical reputation framework with one long-lived player of unknown type and many short-lived players to investor activism. This framework originated in Kreps and Wilson (1982) and Milgrom and Roberts (1982), which study the chain-store stage game, and was generalized to other stage 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 Fig. 1.

Model Figure 1: Stage game tree



M controls a firm with access to a project that would generate an average return for shareholders of $\Delta > 0$. However, M does not take the project without intervention by A because it entails private cost $B > \Delta$. We scale all payoffs for both A and M into units of returns, so they each receive gross payoff of Δ if the project occurs. For M, this implies all payoffs are in units of the firm's initial market value and B can be interpreted as the stock return that would make M indifferent to taking the project. For A, this implies all payoffs are in units of their initial investment in the target firm.

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 to 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 $\tilde{L} > 0$ of an activist campaign. 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)).

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:

$$[\Pi_{A,Settle}, \Pi_{M,Settle}] = \left[\Delta - \tilde{L}, \Delta - B\right]. \tag{1}$$

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 Δ.[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 et al. (2014), Bebchuk et al. (2019)). Therefore, if A chooses *Fight*, the payoffs are:

$$[\Pi_{A,Fight}, \Pi_{M,Fight}] = \left[\Delta - \tilde{L} - \tilde{F}_A, \Delta - B - \tilde{F}_M\right]. \tag{2}$$

If A chooses *Fold*, M ignores the project and the payoffs are:

$$[\Pi_{A,Fold}, \Pi_{M,Fold}] = \left[-\tilde{L}, 0\right]. \tag{3}$$

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 are target or interaction specific, according to:

$$log(\tilde{L}) \sim N\left(\mu_L, \tau_L^{-2}\right), \tag{4}$$

$$log\left(\frac{\tilde{F}_M}{B-\Delta}\right) \sim N\left(\mu_M, \tau_M^{-2}\right), \tag{5}$$

$$log(\tilde{F}_A) \sim N\left(\mu_A, \tau_A^{-2}\right). \tag{6}$$

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

[5] In Online Appendix E, we show our results are robust to a fraction $\phi < 1$ of proxy fights succeeding.

Activists differ only by their μ_A, which takes one of two values: $\mu_{agr} < \mu_{caut}$.[6] When A has $\mu_A = \mu_{agr}$, they are more likely to fight and we therefore refer to them as the **aggressive** type and A with $\mu_A = \mu_{caut}$ as the **cautious** type. 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.

The key information asymmetry in the model is that A knows their type and but M does not and has to estimate it from A's past behavior. 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 $\tilde{F}_A$. All other parameters, including Δ and B, are common knowledge and fixed across campaigns.[7]

3.2. Dynamics

Campaign opportunities arrive exogenously according to a Poisson process with an annualized arrival rate λ_c, which we assume is the same for all activists.[8] 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 δ. Each M is only targeted once, and so simply maximizes their expected payoffs in the current campaign.

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

[6] Another possible difference between types of activists is in their idea quality, which would result in Δ varying across activist. As we detail in Online Appendix B, measures of activist-specific idea quality are less persistent and worse predictors of future campaign success than measures of aggressiveness, suggesting Δ does not vary substantially across activists.

[7] In Online Appendix E, we show allowing Δ to vary randomly across campaigns affects some parameter estimates, particularly for the precision of $\tilde{L}$, but not our estimates of the overall impact of reputation.

[8] 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.

aggressive. It subsequently evolves as time passes and new campaign opportunities arrive.

We assume M does not observe the true outcome of past campaigns by A, but instead only observes the same imperfect indicators we observe as econometricians. This approach closely connects our model to the data because, for a given parameterization, the r_t we compute empirically is the true model r_t. If instead we assumed that M could observe the true outcomes of past activist campaigns, true r_t would become unobservable to us as econometricians and we would need to estimate an evolving distribution of possible r_t for each A rather than just a single time-series, greatly complicating estimation. Furthermore, we argue some degree of noise in M's observation of past campaign outcomes is realistic.

There are two main data limitations M faces, summarized by Model Table 1 and motivated empirically in Section 4.1. The first is they do not observe campaign opportunities A chooses to ignore, instead only observing an indicator (*13-D*) which equals one when a campaign was initiated on each activist-day. As a result, when *13-D* $= 0$, future M are not sure whether no opportunity arrived or one arrived and the activist chose *Ignore*. The second limitation is that while M can directly observe campaigns ending in a *Fight* using indicator variable *Proxy*, they do not perfectly observe whether non-proxy campaigns ended with *Settle* or *Ignore*. Observing long-run target stock returns does not perfectly reveal whether a campaign was settled because Δ is the average return and not the realized return in every successful campaign. Instead, M uses a vector of binary observable actions by the target, denoted $\mathbf{a}$, that are correlated with campaign success in the following way:

$$\mathbb{P}(a_i = 1) = \hat{a}_i + \mathbf{1}(\textit{Settle} \text{ or } \textit{Fight})\beta_i, \tag{7}$$

where a_i is the ith action in vector $\mathbf{a}$, $\hat{a}_i$ is its predicted value in the absence of activism, and β_i is the added probability of action i during a campaign ending in *Settle* or *Fight*. We detail the a_i we use in Section 4.1, and our calibration of $\hat{a}_i$ and β_i in Section 4.3.

Using the indicators *13-D*, *Proxy*, and $\mathbf{a}$, we can solve for the evolution of r_t both between and following observed campaigns using Bayes' rule. After an observed campaign,

Model Table 1: Outcomes observed by future targets

This table summarizes what M observes about past campaigns by A. Observed outcomes are indicator variables *13-D*, which equals one on activist-days when a campaign is initiated; *Proxy*, which equals one when the campaign outcome is *Fight*; and a set of five a_i, each equal to one if the target takes action i. The table provides the values of *13-D* and *Proxy*, as well as the probability $a_i = 1$ ($\mathbb{P}(a_i = 1)$), all of which depend on the true outcome on each activist-day. True outcomes can be no campaign opportunity (*No opportunity*), or a campaign opportunity that ends with *Ingore*, *Fold Settle*, or *Fight*, as described in Section 3.1.

	Observed outcomes		
True outcome	*13-D*	*Proxy*	$\mathbb{P}(a_i = 1)$
No opportunity	0	–	–
Ignore	0	–	–
Fold	1	0	$\hat{a}_i$
Settle	1	0	$\hat{a}_i + \beta_i$
Fight	1	1	$\hat{a}_i + \beta_i$

A's reputation updates to the posterior r_{t+}:

$$r_{t+} = \begin{cases} \mathbb{P}\left(\mu_A = \mu_{agr} | \mathbf{a}, r_t, Proxy = 0\right) & \text{if } Proxy = 0 \\ \mathbb{P}\left(\mu_A = \mu_{agr} | r_t, Fight\right) & \text{if } Proxy = 1. \end{cases} \tag{8}$$

Between campaigns, r_t evolves continuously for two reasons. The first is that, as discussed above, the absence of campaigns indicates a campaign opportunity may have arrived but A chose to *Ignore* it. Because cautious A are more likely to choose *Ignore*, r_t 'decays' with each passing moment as it is increasingly likely A ignored an opportunity. The second reason r_t evolves between campaigns is that 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 λ_r, and are observed by A but not by M. We include them in our model because they cause r_t to 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.[9] See Appendix A for the relevant formulas.

[9]Events affecting activists in our sample consistent with type re-draws include Riley Investment Management's 2009 IPO and Ramius Capital merging with the Cowen Group in 2009.

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

$$V_i(r) \equiv \int_0^\infty \delta^s \lambda_c \mathbb{E}\left(\Pi_i(r_{t+s})|r_t = r, \mu_A = \mu_i\right) ds \tag{9}$$

and $\mathbb{E}\left(\Pi_i(r_{t+s})|r_t = r, \mu_A = \mu_i\right)$ is the expected payoff to an A of type i for campaign 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 A choose *13-D* when a campaign opportunity arises ($d_{caut}(r_t)$ and $d_{agr}(r_t)$, respectively); the probability M chooses *Settle* ($y(r_t)$); and the probabilities that cautious and aggressive A choose *Fight* ($f_{caut}(r_t)$ and $f_{agr}(r_t)$, respectively).

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

$$\tilde{F}_A \leq \Delta + V_i(r_{t+}|\textit{Fight}) - \mathbb{E}\left[V_i(r_{t+})|\textit{Fold}\right] \equiv \overline{F}_i \tag{10}$$

where r_{t+} is A's post campaign reputation and the expected value is taken across possible r_{t+} that can result from different draws of $\mathbf{a}$ conditional on the true campaign outcome being *Fold*. There is no uncertainty about r_{t+} when the true outcome is *Fight* because future targets can directly observe this outcome. Type i's probability of fighting therefore satisfies:

$$f_i(r_t) = \Phi\left(\tau_A^{-1}\left(\log\left(\overline{F}_i\right) - \mu_i\right)\right), \tag{11}$$

where $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution.

M chooses *Settle* when $p_f(r_t)$, the probability A fights given r_t and equilibrium strategies, is sufficiently high relative to their cost of fighting:

$$\underbrace{\Delta - B}_{\Pi_{m,Settle}} \leq \underbrace{(\Delta - B - \tilde{F}_M)}_{\Pi_{m,Fight}} p_f(r_t) \Rightarrow \frac{\tilde{F}_M}{B - \Delta} \geq \frac{1 - p_f(r_t)}{p_f(r_t)} \equiv \overline{F}_M, \tag{12}$$

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.

Eq. (12) shows M's decision depends on $\tilde{F}_M$ relative to $B - \Delta$. We therefore estimate the properties of $\frac{\tilde{F}_M}{B-\Delta}$, parameterized by μ_M and τ_M, but have no way of separating $\tilde{F}_M$ and $B - \Delta$. Eq. (12) implies M's probability of settling satisfies:

$$y(r_t) = 1 - \Phi\left(\tau_M^{-1}\left(\log\left(\overline{F}_M\right) - \mu_M\right)\right). \tag{13}$$

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

$$\begin{aligned} \tilde{L} \leq & - V_i(r_t) + y(r_t)\left(\Delta + \mathbb{E}\left[V_i(r_{t+})|\mathit{Settle}\right]\right) \\ & + (1 - y(r_t))f_i(r_t)\left(\Delta + V_i(r_{t+}|\mathit{Fight}) - \mathbb{E}\left[\tilde{F}_i \,|\tilde{F}_i < \overline{F}_i\right]\right) \\ & + (1 - y(r_t))(1 - f_i(r_t))\mathbb{E}\left[V_i(r_{t+})|\mathit{Fold}\right] \equiv \overline{L}_i. \end{aligned} \tag{14}$$

Eq. (14) implies that the type i's probability of choosing *13-D* satisfies:

$$d_i(r_t) = \Phi\left(\tau_L^{-1}\left(\log\left(\overline{L}_i\right) - \mu_L\right)\right). \tag{15}$$

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_i^s, y^s, and f_i^c for the equilibrium strategies a one-shot stage game, we simplify the cutoff values $\overline{L}_i$ and $\overline{F}_i$ to:

$$\overline{L}_i^s \equiv y^s\Delta + (1-y^s)f_i^s\left(\Delta - \mathbb{E}\left[\tilde{F}_i \,|\tilde{F}_i < \overline{F}_i^s\right]\right), \tag{16}$$

$$\overline{F}_i^s \equiv \Delta. \tag{17}$$

Based on these cutoffs, we compute the static equilibrium strategies that make Eqs. (11), (13), and (15) all hold when using $\overline{L}_i^s$ and $\overline{F}_i^s$ in place of $\overline{L}_i$ and $\overline{F}_i$.

3.5. Model predictions

We illustrate the key predictions of our model with and without reputation in Fig. 1. For the static model, we illustrate how the exogenous likelihood A is aggressive (r_0) affects equilibrium outcomes. The first plot of Fig. 1 shows both types of A have higher likelihood of choosing *13-D* (d^s_{caut} and d^s_{agr}) when r_0 is higher because they are more likely to receive profitable settlements (higher y^s), as illustrated by the second plot of Fig. 1. Finally, the third plot in Fig. 1 shows r_0 has no impact on either type of A's probability of fighting (f^s_{caut} or f^s_{agr}) because their decision has no impact on future campaigns in the static model.

The dynamic model carries through the predictions of the static model but adds two further implications. The first is both types of A initiate more proxy fights than they do in the static model ($f_{caut} > f^s_{caut}$ and $f_{agr} > f^s_{agr}$). These additional fights arise in cases where a proxy fight's cost $\tilde{F}_A$ is more than the direct payoff Δ but justified by the expected increase in future project payoffs. 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 both types of A initiate more campaigns than they do in the static model ($d_{caut} > d^s_{caut}$ and $d_{agr} > d^s_{agr}$). Because aggressive A are more likely to choose *13-D* than cautious A, campaigns on average increase r_t. 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 A expects r_t to change after each potential outcome. We illustrate these effects in the final two plots of Fig. 1. For this parameterization, proxy fights substantially increase r_t, settlements moderately increase expected r_t, and folds slightly increase or decrease expected r_t depending on pre-campaign r_t.[10] The final plot in Fig. 1 shows the value function is much steeper for aggressive A when r_t is low 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 r_t 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.

3.6. Identification in the model

Before turning to the data, we describe the comparative statics and empirical predictions that allow us to identify our model's parameters using observable campaign outcomes. Model parameters are not directly estimable because the realizations of random campaign and proxy fight costs ($\tilde{L}$, $\tilde{F}_M$, and $\tilde{F}_A$) and each activist's evolving reputation (r_t) are not observable. Instead, we observe a panel of activist campaigns including the variables outlined in Model Table 1 (*13-D*, $Proxy$, and $\mathbf{a}$) as well as the target's stock return upon campaign announcement (CAR), as detailed in Section 4.1.

We can identify our model's parameters using a panel of observable campaign outcomes because each parameter has a distinct impact on the model's predictions for how the frequency and outcomes of A's campaigns depend on their track record. This dependence occurs due to reputation: A's history determines their r_t, which in turn determines the observable

[10] Fig. 1 plots expected r_{t+} after *Settle* and *Fold* outcomes across possible realizations of $\mathbf{a}$.

frequency and outcomes of future campaigns. For example, A initiates more campaigns when they have a recent history of proxy fights because those fights increased their r_t. Because our model specifies the functional forms for this and other relations between past and future campaigns, we can estimate the model using maximum likelihood by finding the parameters that best match model-predicted relations to observed empirical relations.

The identification requirement for maximum likelihood estimation (MLE) is that there is a unique parameterization which maximizes the likelihood of observed data. In this section, we show how our model satisfies this condition by showing each parameter's unique impact on the predicted likelihood of observable outcomes. To do so, we first provide economic intuition for the effects of changing each parameter using plots of A and M's equilibrium strategies in Fig. 3. We then translate these comparative statics to empirical predictions for how each parameter affects the likelihoods of observable outcomes in Fig. 4.[11]

Instead of presenting estimates of the means of log costs (μ_L, μ_M, μ_{caut}, and μ_{agr}), which are difficult to interpret, we map these means to probabilities expressing what they imply for equilibrium strategies when $r_t = 0$, as summarized by Model Table 2. 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 $r_t = 0$. With $r_t = 0$, reputation is irrelevant and there is a one-to-one mapping between these four probabilities and the corresponding μ (see Appendix D). This mapping has no effect on the economics of our model, and our results would be the same if we directly estimated the μ instead.

3.6.1. Identifying activists' campaign cost parameters ($d_{caut,0}$ and τ_L)

We primarily identify $d_{caut,0}$ and τ_L using the observed campaign frequency (*13-D*/yr) in the full sample and the difference in *13-D*/yr when activists have strong and weak track records, making r_t unusually high or low. Increasing $d_{caut,0}$ is equivalent to lowering average

[11] Changing any parameter affects equilibrium strategies at all three stages of the activism game and therefore all predicted likelihoods. However, for brevity, Figures 3 and 4 only illustrate the key distinct prediction(s) our model makes about each variables' impact that allow identification. The full set of plots are in Online Appendix Figures 1 and 2.

Model Table 2: Parameters governing random costs in the model and estimation

This table summarizes the parameters governing random costs in our model. Random variables have a tilde and parameters we estimate empirically are boxed. Given other model parameters the mapped parameters are a one-to-one function of the means μ, as specified in Appendix D.

Random cost	Notation	Log distribution Mean	Precision	Mapped Parameter
A campaign cost	$\tilde{L}$	μ_L	$\boxed{\tau_L}$	$\boxed{d_{caut,0}} = \mathbb{P}(\textit{13-D} \vert r_t = 0, \mu_L)$
M relative fight cost	$\frac{\tilde{F}_M}{B-\Delta}$	μ_M	$\boxed{\tau_M}$	$\boxed{y_0} = \mathbb{P}(\textit{Settle} \vert r_t = 0, \mu_M)$
Caut. A fight cost	$\tilde{F}_A$	μ_{caut}	$\boxed{\tau_A}$	$\boxed{f_{caut,0}} = \mathbb{P}(\textit{Fight} \vert r_t = 0, \mu_{caut})$
Agr. A fight cost	$\tilde{F}_A$	μ_{agr}	$\boxed{\tau_A}$	$\boxed{f_{agr,0}} = \mathbb{P}(\textit{Fight} \vert r_t = 0, \mu_{agr})$

campaign costs, meaning both types of A choose *13-D* more frequently across all r_t (denoted by higher d_{caut} and d_{agr}), as illustrated by the top left plot in Fig. 3. Increasing τ_L decreases the noise in $\tilde{L}$, making A put relatively more weight on the expected payoff in the campaign. The second plot in the first row of Fig. 3 shows this leads aggressive A, who have higher expected payoffs, to initiate more campaigns across all r_t. It also makes cautious A initiate more campaigns when r_t is high because the higher likelihood of settling increases their expected payoff, but has no effect on d_{caut} for low r_t because $d_{caut,0}$ is fixed.

The first two plots of in the top row of Fig. 4 show these comparative statics translate to the empirical prediction that $d_{caut,0}$ and τ_L determine the level and slope, respectively, of the relation between r_t and the model-implied *13-D*/yr. Note that all plots in Fig. 4 show predictions for r_t between 0% and 10% to make level and slope effects easier to visually distinguish and because, as described below, we estimate the median r_t is 0.55% and 75% of r_t are below 10%.

3.6.2. Identifying targets' proxy fight cost parameters (y_0 and τ_M)

We primarily identify y_0 and τ_M using the average settlement frequency and the difference in settlement frequency when activists have strong versus weak track records, respectively. Increasing y_0 is equivalent to increasing M's average cost of a proxy fight, which increases the probability M settles across all r_t, as illustrated by the first plot in the second row of Fig. 3. Increasing τ_M reduces the noise in M's settlement decision and therefore increases the sensitivity of y to r_t, as illustrated by the second plot in the second row of Fig. 3. These comparative statics translate directly to predictions about the probability a campaign is settled ($\mathbb{P}(Settle)$), as illustrated by the first two plots in the second row of Fig. 4. We use observable target actions $\mathbf{a}$ to measure *Settle* empirically, as detailed in Model Table 1.

3.6.3. Identifying activists' proxy fight cost parameters ($f_{caut,0}$, $f_{agr,0}$, and τ_A)

We primarily identify $f_{caut,0}$ using the full-sample probability campaigns end in proxy fights. Increasing $f_{caut,0}$ is equivalent to reducing cautious A's average cost of a proxy fight, and therefore increases the probability cautious A choose *Fight* when refused, as illustrated in the first plot of the final row in Fig. 3. The same plot illustrates aggressive A choose *Fight* slightly less frequently with higher $f_{caut,0}$ because cautious A's added aggression decreases the reputation gained by choosing *Fight*. The bottom left plot in Fig. 4 shows that these effects shift the probability of a proxy fight ($\mathbb{P}(Fight)$) upwards for A with low r_t, which drives up the predicted full-sample average because we estimate most A have low r_t.

We primarily identify $f_{agr,0}$ using the differences in settlement and proxy fight frequencies between low and high r_t subsamples. Increasing $f_{agr,0}$ while holding fixed $f_{caut,0}$ widens the gap between cautious and aggressive A in their frequency of proxy fighting (see the third plot of the third row in Fig. 3). This added difference also increases the slopes of the relations between r_t and both initiation and settlement decisions (see the third plots in the first and second rows of Fig. 3). Combined, these comparative statics yield a distinct empirical prediction for $f_{agr,0}$: it positively affects the slope of the relations between r_t and *13-D*/y, $\mathbb{P}(Settle)$, and $\mathbb{P}(Fight)$, as illustrated by Fig. 4. Other variables increase one of these slopes but not the others – for example, Fig. 4 shows that increasing τ_M increases $\mathbb{P}(Settle)$ when r_t is high but *decreases* $\mathbb{P}(Fight)$ because fewer campaigns reach that stage. The unique prediction that allows to identify τ_M is therefore that it positively affects both the r_t–$\mathbb{P}(Settle)$ relation and the r_t–$\mathbb{P}(Fight)$ relation.

We primarily identify τ_A using the frequency and success of campaigns after r_t has recently been updated. Increasing τ_A decreases the noise in A's decision to fight, leading them to initiate more fights as investments in reputation, which in turn results in more settlements by M and more campaign initiations by cautious A, as illustrated by the fourth column of plots in Fig. 3. These effects combine to make increasing τ_A result in a higher $\mathbb{P}(Settle)$ and $\mathbb{P}(Fight)$ for moderate r_t (but no change for extreme r_t), and smaller increases in r_t following successful campaigns because the relative aggressiveness of aggressive A (d_{agr}/d_{caut} and f_{agr}/f_{agr}) is smaller. The fourth column of plots in Fig. 4 illustrate both these effects. As we discuss in Section 5.2, the reputation-updating prediction is more distinct from the effects of other parameters and therefore plays a larger role in identifying τ_A.

3.6.4. Identifying remaining parameters (r_0, λ_r, and Δ)

We primarily identify r_0 by comparing campaigns by A with little or no track record to the broader sample. Increasing r_0 directly affects the function mapping past observed campaigns to r_t by increasing the prior used for Bayesian updating, resulting in higher r_t for all observations but especially when the activist is new to the sample and more weight is on the prior. Our choice of r_0 therefore primarily affects the relative likelihoods of campaign initiation and success in the subsample of inexperienced activists.[12]

We identify λ_r using the apparent degree of persistence in the relation between past and future campaign outcomes. The arrival rate of type resets (λ_r) directly affects the mean reversion in r_t when A does not initiate a campaign, as described in Section 3.2 and plotted in Online Appendix Fig. 2. We therefore predict λ_r primarily affects model implications for observations where A had high r_t prior to a period of inactivity, meaning r_t is decaying.

One other parameter requires the full structure of the model to estimate: the value added for target shareholders in a successful campaign (Δ). For a given Δ, our sample of campaign outcomes allows us to identify the distribution of costs and reputation as described above. However, campaign outcome variables do not pin down the scale of successful projects. Instead, we identify Δ using the model's prediction for the expected return to

[12]For brevity and because they are straightforward to describe, we do not plot the effects of r_0, λ_r, and Δ in Figures 3 and 4. We provide and discuss these plots in Online Appendix D.

target shareholders at the start of a campaign:

$$\mathbb{E}(\text{Target shareholder payoff}|r_t, \textit{13-D}) = \Delta \cdot \mathbb{P}(\text{project occurs}|r_t, \textit{13-D}). \tag{18}$$

We can therefore identify Δ by combining model-implied campaign success rates with observed stock market reactions to campaign announcements (CAR). These reactions also serve as an extra source of identifying variation as Eq. (18) predicts how they vary across campaigns as a function of r_t.

In summary, we identify the ten parameters:

$$\theta = [\Delta, d_{caut,0}, \tau_L, y_0, \tau_M, f_{caut,0}, f_{agr,0}, \tau_A, r_0, \lambda_r] \tag{19}$$

using the structure of the model to fit observed relations between past and future campaign frequency, outcomes, and announcement returns. In Section 4.3, we describe how we implement this identification strategy for θ using maximum likelihood and how we calibrate the remaining model parameters.

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.[13] 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-Center for Research in Securities Prices (CRSP) Linked data and we identify the activist is a financial institution.[14] We exclude campaigns for which the target security does not pertain to an operating corporation by requiring

[13] The SEC requires that investors file a 'beneficial ownership report' on Form 13-D within ten days of initiating an activist campaign.

[14] To filter individual and non-financial corporation activists, we drop 13-D filings in which the activist Central Index Key (regcik) has no 13-F filings on Edgar, and drop SharkWatch campaigns in which the activist is classified as "Corporate" or "Indiv". We match target firms to Compustat-CRSP using CIKs and quarterly filing dates for the 13-D filings and 9-digit CUSIPs and quarterly filing dates for the SharkWatch campaigns.

target CRSP share code be 10, 11, 18, 31, or 71, and dropping campaigns targeting firms with Standard Industry Classification (SIC) codes 6770 and 6726 (closed-end mutual funds and Special Purpose Aquisition Companies (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 et al. (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 ($Proxy = 1$) attributable to a single activist, we select that activist as the lead for the campaign.[15] 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 et al. (2010)) and who have the institutional structure most favorable to taking the costly actions required to build and maintain reputation (see Starks (1987), Ackermann et al. (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 Online Appendix G, we analyze the remaining 1,801 campaigns by 603 unique non hedge fund activists targeting 1,489 unique firms.

[15] We compute $Proxy$, an indicator for whether the campaign features a proxy fight, by collecting preliminary and definitive proxy filings from Edgar relating to contested solicitations: forms DFAN 14A, DEFR 14A, DEFC 14A, and DEFN 14A, and apply the matching and filters outlined above with 13-D filings. For SharkWatch campaigns, we also use the provided "proxy fight" designation.

We face two data limitations that guide our sample construction and, because we assume future targets face the same limitations, the modelling choices discussed in Section 3.2. The first is that we cannot observe instances in which an activist identified a potential target but chose not to initiation a campaign. The second is that there is no direct measure for whether a campaign was settled. In principle, one could use the text in 13-D filings to determine specific demand(s) made by activists and then use subsequent news items and financial statements to see whether those demands were met. However, successful campaigns often end with different outcomes than those specified in the 13-D filing because initial demands are often vague (e.g. 'enhance shareholder value') and serve as the start of a broad and evolving negotiation. Furthermore, Bebchuk et al. (2019) finds evidence formal legal settlements are relatively rare, occurring in only 13% of their sample, but informal settlements whereby targets take activist-friendly actions are much more common. We therefore include all campaigns in our sample regardless of initial demands, and use the vector $\mathbf{a}$ of observable actions by the target to assess whether non-proxy campaigns are formally or informally settled.

The five variables in $\mathbf{a}$ 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. We compute these five indicators using 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 $\hat{\mathbf{a}}$ as the fitted value from these regressions for the target at the time of campaign initiation. Using $\hat{\mathbf{a}}$ that vary across campaigns allows us to address the possibility that high reputation activists seem more successful by our measures because they select firms that will take the actions $\mathbf{a}$ even without activist intervention. Using $\hat{\mathbf{a}}$ mitigates this possible explanation because it requires activist campaigns prompt targets to take more target actions than their characteristics would predict. As a robustness test, we show in Online Appendix E that assuming constant $\hat{\mathbf{a}}$ across all campaigns has a negligible effect on our results.

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 firms around the day on which the campaign is initiated.

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 by $\hat{\mathbf{a}}$ 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 *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.

[[Insert Table 1 about here]]

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 average $AbActions$ in these campaigns is 0.649, around 40% of the total in $Proxy = 1$ campaigns.

Table 1 also 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 use two vectors to summarize our model's parameters:

$$\theta = [\Delta, d_{caut,0}, \tau_L, y_0, \tau_M, f_{caut,0}, f_{agr,0}, \tau_A, r_0, \lambda_r] \,, \tag{20}$$

$$\Omega = [\delta, \sigma_{car}, \beta_{reorg}, \beta_{payout}, \beta_{ceo}, \beta_{board}, \beta_{acq}, \lambda_c] \,, \tag{21}$$

where σ_{car} is the standard deviation of CAR. The first ten parameters (θ) are difficult to estimate directly but can be identified using the structure of the model combined with our panel of campaigns, as illustrated in Section 3.6. The remaining eight parameters (Ω) are either impossible to separately identify using available data or are estimable without the model. We therefore fix Ω and estimate θ using maximum likelihood (MLE).

We assign a value for δ because we cannot distinguish empirically between a high value of δ, which makes activists initiate more campaigns and proxy fights as investments in reputation, and higher values of campaign cost precision τ_L and manager proxy cost precision τ_A, which have the same two effects, respectively. We therefore base our estimation on the assumption that $\delta = 0.9$.[16] Similarly, we cannot distinguish empirically between a high arrival rate λ_c, which makes observed campaigns occur more frequently, and a high no-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 ($d_i(r_t) \leq 1$) is far from binding. In Online Appendix E, we show our main results are robust to alternative choices for these exogenous parameters as long as λ_c is not unrealistically small.

Unlike the parameters in θ, both σ_{car} and β_i are estimable using reduced form approaches that do not rely on the structure of the model. For σ_{car}, we use the sample standard deviation of CAR, 8.99%. Our estimates for β_i, the added probability of action a_i due to a successful campaign, rely on the definition provided in Eq. (7). This definition shows β_i equals the average $a_i - \widehat{a}_i$ in campaigns featuring a proxy fight, which we present in Table 1. We account for first-stage estimation error in σ_{car} and β_i when calculating standard errors for our estimates of θ, as detailed in Online Appendix C.

Given these fixed values for Ω, we estimate θ by maximizing the likelihood of observed data. For each θ, we compute the likelihood function $l(\theta)$ using the following process:

1. Compute equilibrium strategies and value functions numerically as described in Section 3.3 and Appendix A.
2. Using these strategies, compute each activist's reputation r_t for each day, as described in Section 3.2 and Appendix A.
3. Compute the conditional likelihood of each observed campaign as follows:

$$\mathsf{L}_c(\theta) = \mathsf{L}_c^{gap}(\theta) \cdot \mathsf{L}_c^{13-D}(\theta) \cdot \mathsf{L}_c^{car}(\theta) \cdot \mathsf{L}_c^{outcome}(\theta), \tag{22}$$

   where $\mathsf{L}_c^{gap}(\theta)$ is the probability the activist initiates no campaigns until the date of their next *13-D*, $\mathsf{L}_c^{13-D}(\theta)$ is the probability an opportunity arrives on the date of campaign c and the activist chooses *13-D*, $\mathsf{L}_c^{car}(\theta)$ is likelihood of the target stock's reaction to the campaign initiation (CAR), and $\mathsf{L}_c^{outcome}(\theta)$ is the likelihood of the observed outcomes

[16]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)).

$Proxy_c$ and $\mathbf{a}_c$ conditional on campaign initiation. Each of these likelihoods depends on r_t, as detailed in Appendix D. We assume CAR has distribution:

$$CAR \sim N\left(\Delta \cdot \mathbb{P}(\text{project occurs}|r_t, \textit{13-D}), \sigma^2_{car}\right). \tag{23}$$

4. Compute overall likelihood $\mathsf{l}(\theta) = \sum_c \log\left(\mathsf{L}_c(\theta)\right)$.

5. Results and counterfactuals

5.1. Equilibrium results and hypothesis tests

Panel A of Table 2 presents our estimates of model parameters along with standard errors accounting for estimation error in σ_{car} and β_i and confidence intervals based on likelihood ratio tests. Fixing any individual parameter to take a value outside these ranges results in a significantly worse fit at the 5% even when all other parameters are re-estimated maximize fit, as detailed in Online Appendix C.

[[Insert Table 2 about here]]

We find that the projects activists demand generate average return $\Delta = 6.62\%$ for target shareholders. 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 98% of activists are cautious and therefore are likely to remain cautious after their type is re-drawn.

Our estimated parameters imply the mean campaign cost ($\tilde{L}$) is 5.44% of the activist's position in the target, while the mean proxy fight cost ($\tilde{F}_A$) 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.

The only other estimates of these costs we are aware of are in Gantchev (2013), which finds non-proxy campaigns cost an average of 5.05% of the activist's investment and proxy fights cost an additional 8.27%. These averages differ from ours in sample period, data sources, and estimator. However, there is a potential economic reason the average costs in Gantchev (2013) are lower than our estimates, especially for cautious A: his static framework requires all decisions be profitable in a single campaign, whereas our dynamic framework allows activists to initiate campaigns and proxy fights at a loss as an investment in reputation.

For a given set of no-reputation parameters $d_{caut,0}$, y_0, $f_{caut,0}$, and $f_{agr,0}$, the precision parameters τ_L, τ_M, and τ_A determine how agents behave when r_t is strictly positive. Large values of τ_L and τ_M indicate stronger relations between r_t and campaign initiation and settlement decisions, respectively. Large values of τ_A indicate more reputation-seeking fights. Small values of these precisions indicate agents follow mixed strategies independent of their r_t. We find that all three precisions are positive and statistically distinct from zero, indicating that constraining our model to ignore r_t at any of the three stages results in significantly worse fit. We illustrate the economic significance of these precisions in Fig. 1, which presents estimated equilibrium strategies as a function of r_t, 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's 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 in Section 3.4 with the unconditional reputation r_0 applying in all campaigns. This implies all stage games follow the same mixed strategy equilibrium, where A with type i chooses *13-D* with probability

d_i^s and *Fight* with probability f_i^s, and M chooses *Settle* with probability y^s. While we can identify these equilibrium probabilities, we cannot identify the full set of parameters θ in a no-reputation world because many θ 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: Δ, $d_{caut,0}$, y_0, and $f_{caut,0}$.

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 Fig. 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 show below, r_t strongly predicts campaign frequency and outcomes. We therefore find a high likelihood ratio χ^2 statistic and strongly 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 θ except for τ_A (because r_t is never between zero and one) and λ_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.[17] 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 r_t 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.

5.2. Moments and identification in the data

In Section 3.6, we discuss our identification strategy in the context of our model, showing how parameters affect the predicted relations between past and future observable outcomes via r_t. In this section, we illustrate how our model's parameters are identified using our sample, and various sub-samples, of activist campaigns. To do so, we compute moments in the data, predicted values for these moments in baseline and alternative models, and the elasticity of model-predicted moments with respect to changes in parameters.

The moments, presented in Table 3, are the means of four outcome variables (*13-D*, $AbActions|Proxy = 0$, CAR, and $Proxy$) in the full sample, and differences in means across subsamples selected based on the analyses in Section 3.6. The four subsample differences we present are: high r_t observations (those with $r_t > 50\%$) minus low r_t observations (those with $r_t < 0.5\%$); observations with recently updated r_t (those where A has five or more campaigns and an increase in r_t over the prior year) minus the full sample; observations with new A (those in each A's first year) minus the full sample; and observations with decaying r_t (those with $r_t > r_0$ and over a year since the prior campaign) minus the full sample.

[[Insert Table 3 about here]]

[17] Aggressive A's probability of choosing *13-D* and M's probability of settling with aggressive A, are computed from full-information $d_{caut,0}$, τ_L, y_0, and τ_M.

5.2.1. *Alternative models*

For both our baseline model and alternative models, we use estimated parameters presented in Table 2 to compute each activist's r_t for all days, including days without campaign initiations.[18] For each campaign in our sample, we then compute the model-implied average $Ab\,Actions|Proxy = 0$, CAR, and $Proxy$ conditional on pre-campaign r_t. For the model-implied moments of *13-D*, we use r_t on all activist-days to compute the likelihood we observe a *13-D* on each activist-day. Finally, we compute average model-predicted values across the full sample and differences in averages across subsamples.

We find our baseline model fits the means of *13-D*, CAR, and $Proxy$ well, but underestimates the mean of $Ab\,Actions|Proxy = 0$. Our baseline model also fits cross-reputation differences well for *13-D*, slightly overstates differences in $Ab\,Actions$, and understates cross-reputation differences in $Proxy$. We discuss model fit extensively in Section 5.4.

In Table 3, we also show the predicted values for each moment in the no-reputation and full-information alternative models, with $\uparrow$ ($\downarrow$) superscripts indicating moments which the alternative model fits significantly better (worse) than the baseline model. The no-reputation alternative fits the full-sample means well but predicts no cross-campaign variation in expected outcomes, making all its predictions for difference-based moments equal to zero. This results in the no-reputation model fitting four of the moments based on cross-campaign differences significantly worse than our baseline model, illustrating why our formal likelihood-ratio test rejects the no-reputation alternative in Table 2.

There are no significant differences between our baseline model and the full-information model in fitting the moments in Table 3, with one notable exception: the spread in *13-D* between high and low r_t observations, which the full-information model fits significantly worse than our baseline model. As we detail in Section 5.4, the full-information model fails to capture the full extent of variation in *13-D* because it only allows across-activist variations, whereas our model also allows within-activist variation depending on r_t. This shortcoming,

[18] See Appendix D for details on how we handle activists only present in part of our sample.

together with the additional within-activist evidence we discuss in Section 5.4, lead to the rejection of the full-information alternative in Table 2.

5.2.2. Identifying parameters in the baseline model

In Section 3.6 we illustrate how each model parameter has a unique impact on our model's empirical predictions that allows it to be identified. We quantify these predictions in Table 3 by presenting the local elasticities of model-implied values for each moment ($\hat{m}_i$) with respect to each parameter (θ_j), defined as:

$$\text{Elasticity of } \hat{m}_i \text{ wrt parameter } \theta_j \equiv \frac{\partial \hat{m}_i(\hat{\theta})}{\partial \theta_j} \cdot \frac{\hat{\theta}_j}{\hat{m}_i(\hat{\theta})}. \tag{24}$$

We compute these elasticities at our parameter estimate $\hat{\theta}$ for every i and j, but for parsimony we only present elasticities with absolute values above 0.25 in Table 3.

The first column of Table 3 shows elasticities with respect to Δ, which as we describe in Section 3.6 directly affects average CAR. We show this is indeed the case, with average model-predicted CAR having an elasticity with respect to changes in Δ equal to one, which is higher than any other parameter. Furthermore, changing Δ only significantly affects mean CAR, meaning Δ is primarily identified by the sample average CAR.

Consistent with Fig. 4, Table 3 shows $d_{caut,0}$ and τ_L both directly affect mean predicted *13-D*, but τ_L has a larger impact on the predicted difference in mean *13-D* between high and low r_t observations. Other parameters also affect these moments, however $d_{caut,0}$ and τ_L are unique in the sense that other parameters either do not affect both moments (e.g. y_0) or have large effects on moments unrelated to $d_{caut,0}$ and τ_L (e.g. $f_{caut,0}$). We therefore conclude $d_{caut,0}$ and τ_L are primarily identified using observed means of *13-D* in the full sample and subsamples with high or low r_t.

We identify y_0 using a similar approach to $d_{caut,0}$ but with our measure of settlement frequency (average $Ab\ Actions|Proxy = 0$) replacing *13-D* as the outcome variable. Consistent with the prediction in Fig. 4, y_0 is the only parameter to strongly affect the full-sample average of $Ab\ Actions|Proxy = 0$, allowing us to identify y_0 primarily using this moment.

In Section 3.6, we outline our model's predictions for the effects of changing τ_M and $f_{agr,0}$ on the likelihoods of both settlements and proxy fights. Consistent with these predictions, Table 3 shows that increasing τ_M widens the gap in $Ab\,Actions|Proxy = 0$ across high and low r_t campaigns. These added settlements reduce the likelihood of observing $Proxy = 1$ because fewer campaigns reach the final stage, weakening the r_t–$Proxy$ relation. Increasing $f_{agr,0}$ has the opposite effect on the r_t–$Proxy$ relation, which strengthens as aggressive A are more likely to choose *Fight*, but has the same positive effect on the r_t–$Ab\,Actions|Proxy = 0$ relation. Our estimates of τ_M and $f_{agr,0}$ are therefore primarily identified by the observed differences in settlement and proxy fight frequency between high and low r_t subsamples.

Table 3 shows that, consistent with the prediction in Fig. 4, the full-sample mean of $Proxy$ is increasing in $f_{caut,0}$ and not strongly affected by other parameters. Our estimate of $f_{caut,0}$ is therefore primarily identified by this moment.

Figures 3 and 4 show that increasing τ_A narrows the gap in campaign and proxy fight frequency between cautious and aggressive A, making r_t update less dramatically following successful campaigns. This manifests in the model predicting campaigns are less-likely to be initiated or to succeed when τ_A increases in cases where A's reputation has recently updated upwards. We therefore focus on the subsample where A has five or more campaigns in the past year and higher r_t than a year ago, making r_t recently updated and more sensitive to changes in τ_A. The τ_A column illustrates this pattern, with all three relative moments for the recently updated subsample decreasing in τ_A. Table 3 also shows that increasing τ_A affects other moments, however its impact on observations with recently updated r_t is unique in the sense that other parameters either do not affect all three of these moments (e.g. τ_L) or have large effects on moments unrelated to τ_A (e.g. $f_{agr,0}$).

As discussed in Section 3.6, we predict r_0 primarily affects outcomes early in an activist's career. Table 3 shows this is the case, with increases in r_0 causing increases in model-implied settlements and proxy fights by activists in their first year but not significantly affecting overall mean outcomes. We therefore primarily identify r_0 by comparing campaigns early in activist's careers relative to the overall sample.[19]

Finally, increasing λ_r primarily affects the rate at which r_t reverts towards r_0 between campaigns. As a result, Table 3 shows that increasing λ_r only substantially affects moments in situations where there is a long gap since the prior campaign (more than a year) and r_t is still above r_0, meaning r_t is reverting downwards and will be further lowered by increasing λ_r. We therefore primarily identify λ_r using this subset of observations.

The analyses in Table 3 highlight an important aspect of our MLE approach: it 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 r_t as well as the full shape of its relation with campaign frequency and three partially independent outcome measures ($\mathbf{a}$, 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 5.4.

5.3. Reputation in the data

Our estimation procedure produces pre- and post-campaign reputation measures r_t and r_{t+} for each campaign, as summarized by Table 4. Because aggressive activists are rare unconditionally ($r_0 = 2.05\%$), r_t and r_{t+} are positively skewed across campaigns. Most r_t are negligible, with a median of only 0.55%. A few activists establish strong reputations, and initiate campaigns more frequently once they do, making the mean r_t equal to 10.81%.

[[Insert Table 4 about here]]

Panel B of Table 4 shows the top 25 activists by average pre-campaign r_t. 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

[19] Note that changes r_0 have the weakest effects on the moments in Table 3, making r_0 the most difficult to precisely identify empirically. As a result, r_0 has the largest relative standard error in Table 2.

actions, and have average r_t above the 90th percentile of the overall distribution. Fig. 2 shows these the evolution of these activists' r_t, both of which are above 75% for the past decade and peak above 99%. The third plot of Fig. 2 also shows the evolution of r_t for Loeb Partners, who has only initiated one proxy fight, has a low r_t for most of the sample, and extracts many fewer settlements than Icahn Enterprises and Starboard Value.

As illustrated by Fig. 2, r_t is persistent but decays between 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, Fig. 2 shows activist behavior appears to have occasional 'regime shifts' whereby an activist with consistently high or low r_t suddenly changes behavior and r_t. Both Icahn Enterprises and Starboard Value were less frequent and successful activists, and as a result had r_t below 20%, until around 2005, at which point their behavior changed and r_t grew. Another example of this phenomenon is Riley Investment Management, who Fig. 2 illustrates built a strong r_t from 2005–2009 and then suddenly became inactive, possibly due to their parent company's 2009 IPO, initiating only one additional campaign in 2013.

5.4. 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 distributions of outcomes, and comparing these predictions to observed outcomes. We do so using the same process we use for Table 3, described in Section 5.2. However, instead of presenting local elasticities of moments to parameters, we present levels of model-implied and data moments for gradations of r_t and, more importantly, estimates of unobservable equilibrium strategies and motivations gleaned from our estimated model.

Panel A of Table 5 shows that our model predicts activists initiate an average of 1.00 campaigns per year, and that high r_t 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 r_t 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.

[[Insert Table 5 about here]]

Our structural approach also yields estimates for 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 $\tilde{L}$ low enough to initiate a campaign in the dynamic model and compare this to the likelihood of drawing $\tilde{L}$ low enough the expected profit from the individual campaign is positive. From this comparison, we estimate 80.08% of *13-D* decisions in our sample had positive expected single-campaign profits, while the remaining 19.92% were due to reputation-building incentives.

Panel B of Table 5 summarizes strategies, outcomes, and motivations pertaining to settlement and fighting decisions conditional on a campaign initiation. Our estimated model activists with high r_t receive settlements 44.11% of the time compared to only 23.86% of the time for low r_t activists, as depicted in the second plot of Fig. 1. This translates into a strong relation between r_t and the average *Ab Actions* 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 r_t activists but underestimates the success of low r_t 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 *Ab Actions* in all campaigns. The data support the predicted directions of these relations, but imperfectly match the predicted quantities. Both low and high r_t activists receive more average *Ab Actions* than predicted by our model, with only medium r_t campaigns matching the model closely. The model fits average CAR quite well (2.80% vs. 2.82%), but the difference between high and low r_t 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 motivated by reputation building. This fraction is slightly lower than the corresponding fraction of campaign initiations (19.92%) despite proxy fights having a larger impact on post-campaign r_t because our estimates indicate proxy fighting costs are noisier than campaign initiation costs ($\tau_A < \tau_L$). As a result, the cost of fighting $\tilde{F}_A$ is 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. However, they offer several advantages over the summary statistics in Table 5: they allow us to assess which dimensions of the data the model fits well, compare our results to other empirical work on activism, and control for other potentially relevant activist characteristics.[20]

Table 6 present linear regression coefficients for predicting *13-D*, *Ab Actions*, CAR, and $Proxy$ using r_t, without activist fixed effects in Panel A and with them in Panel B. In both Panels A and B, we test three null hypotheses based on whether the data are generated by the baseline model, the no-reputation alternative model, and the full-information alternative model, all estimated to fit the data as well as possible (as detailed in Section 5.1). For each null hypothesis, we compute the average coefficient in 25,000 simulated samples under the null, and test whether the coefficient in the data is different from this average using t-statistics with standard errors clustered by activist.

[[Insert Table 6 about here]]

With the exception of $Proxy$ in Panel A and CAR in Panel B, the magnitude of the estimated coefficients are close enough to the model-predicted magnitudes that we fail to reject the model null, suggesting the model fits fairly well along these dimensions. Echoing the results in Table 5, 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

[20] Other structural papers using reduced form regressions on structurally estimated parameters to illustrate their results include DeAngelo et al. (2011) and Li et al. (2016).

changing a parameter such as τ_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.

Tables 5 and 6 show that the empirical relation between r_t and CAR is weaker than the model-implied relation. One potential reason is that market prices do not react to the information contained in campaign initiations entirely during the [−1,+1] announcement window we focus on. Instead, targets of high reputation activists could outperform targets of low reputation activists prior to the announcement window due to information leakage, or after the announcement window due to a delayed reaction. In Online Appendix F, we show this is the case, with only around a third of the total effect of reputation on target returns occurring during the narrow announcement window.

Unlike the estimated model, we can strongly reject the no-reputation null hypothesis in both Panels A and B. This null predicts no relation between r_t and campaign outcomes, meaning it is rejected by the strong positive relations we find in Panel A. In Panel B, we reject the no-reputation null for predicting *13-D* and *Ab Actions* in part because our simulations reveal that, despite no true relation between r_t and campaign outcomes, regressions with activist fixed effects have *negative* average coefficients in simulated samples. The reason is that these outcome variables are positively correlated with innovations in r_t, meaning regressions with activist fixed effects are biased downwards in finite samples.[21] This small-sample bias disappears with enough campaigns per activist, however 94% of activists have 20 or fewer campaigns in our sample, making it acute in this setting.

Panel A of Table 6 shows the full-information null hypothesis can fit cross-activist differences in outcomes fairly well, though the relation between r_t and campaign frequency is stronger in the data than this null predicts. Consistent with our discussion of Table 2, the full-information null is rejected by the within-activist relations we find in Columns (1) and (2) Panel B, which are significantly larger than the negative coefficients we find in full-

[21]The technical reason for this bias is that these regressions fail the strict exogeneity condition discussed in Wooldridge (2010) and Grieser and Hadlock (2019).

information simulations. The combined evidence in Panels A and B of Table 6 illustrate why the likelihood ratio test presented in Table 2 reject the full-information alternative model in favor of our baseline model: while both models fit many features of the data well, the full-information alternative struggles along more dimensions than our reputation model. Specifically, full-information null is rejected at the 5% level in three of the specifications in Table 6, while the model null is rejected at the 5% level in only one.

In Panel C of Table 6, we include several time-varying activist characteristics as controls. Two variables, *Prior Campaigns* and *Top HF*, mimick the experience and reputation measures used in Boyson et al. (2016) and Krishnan et al. (2016), respectively. Three other variables, $Past\ CAR_{250}|Proxy$, $Past\ CAR_{250}|Hi\ Act$, and $Past\ CAR_{250}$, measure activist-specific idea quality using long run target returns in past campaigns with $Proxy = 1$, past campaigns with above median $Ab\,Actions$, and all past campaigns, respectively. The remaining controls represent potential confounding effects for our results in Panel A, for example the possibility that high r_t 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 increasing in four of the five specifications.

5.5. Counterfactuals

Having analyzed the role of reputation in equilibrium activism, we now estimate how this equilibrium would change in a world without reputation.[22] 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'

[22]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.

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.

We estimate equilibrium behavior and payoffs in the baseline model and each counterfactual by simulating 25,000 samples as detailed in Appendix D. Table 7 presents average behavior at each stage and average payoffs to target shareholders and activists per campaign opportunity.[23] 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 counterfactuals with no aggressive A and full-information 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.

[[Insert Table 7 about here]]

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 7 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 return of Δ if it does. Target

[23]Because we only estimate the distribution of target managers' cost of proxy fights ($\tilde{F}_M$) relative to their net private costs of the project ($B - \Delta$) we cannot quantify managers' payoffs in absolute terms.

shareholders' average payoff 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 7 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 full information because M knows their type and therefore settles even less than in the no-reputation counterfactual. Aggressive A, by contrast, benefit from the full-information counterfactual because M knows their type and therefore chooses *Settle* more frequently.

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).

5.6. Robustness

We conduct robustness tests by re-estimating our model under a variety of alternative parameterizations, empirical implementations, and modelling assumptions. As detailed in Online Appendix E, we consider different values for activists' discount factor (δ) and the arrival rate of campaign opportunities (λ_c); a wider 20-day window for measuring the market's reaction to campaign announcements (CAR); fixed values for the action likelihoods in the absence of activism ($\hat{\mathbf{a}}$); random variations across campaigns in the expected return for target shareholders after a successful campaign (Δ); and proxy fights succeeding only a fraction ϕ of the time.

We find that parameter estimates can sometimes vary due to changes in assumed parameters or model structure. For example, increasing the campaign opportunity arrival rate λ_c results in proportionally smaller estimates of the baseline frequency with which activists choose *13-D* ($d_{caut,0}$). Similarly, random variations in Δ serve as substitutes for random variation in campaign costs ($\tilde{L}$), resulting in higher estimates of their precision (τ_L).

More importantly, we find that our main economic results are consistent across alternative assumptions. Specifically, we find reputation-building incentives explain 15–30% of observed aggressive behavior, and without reputation activists would create 35%–60% less value for target shareholders.[24] The reason these effects are more consistent is they are identified off the changes in average campaign frequency and outcomes as a function of reputation observed in the data. While the specific parameters generating this increase may vary across specification, the economic conclusion remains unchanged.

6. Conclusion

We argue 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 r_t 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 high value projects, negotiating advantageous settlements, and many other skills. Future

[24]The only exception is if we decrease λ_c below the rate at which we observe the highest-reputation activists initiating campaigns – around five per year – which effectively forces reputation effects to be smaller.

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:

$$dr_t = \underbrace{-\frac{\lambda_c(d_{agr}(r_t) - d_{caut}(r_t))r_t(1-r_t)}{\lambda_c(1-d_{caut}(r_t))(1-r_t) + \lambda_c(1-d_{agr}(r_t))r_t + (1-\lambda_c)}dt}_{\text{decay due to absence of campaigns}} + \underbrace{(r_0 - r_t)\lambda_r dt}_{\text{type resets}}, \tag{25}$$

The evolution due to type resets is the product of their arrival rate λ_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:

$$\mathbb{P}(agr|r_t, no\ camp.) - r_t = \frac{\mathbb{P}(no\ camp.|r_t, agr)r_t}{\mathbb{P}(no\ camp.|r_t, agr)r_t + \mathbb{P}(no\ camp.|r_t, caut)(1-r_t)} \tag{26}$$

$$= \frac{[(1-d_{agr}(r_t))\lambda_c + (1-\lambda_c)]\, r_t}{[(1-d_{agr}(r_t))\lambda_c + (1-\lambda_c)]\, r_t + [(1-d_{caut}(r_t))\lambda_c + (1-\lambda_c)]\,(1-r_t)} - r_t, \tag{27}$$

which simplifies to the value given in Equation (25).

Because we do not observe how long an activist is seeking campaign opportunities prior to their first campaign, we do not know how much their reputation evolves from r_0 prior to the first campaign. We assume it evolves to $\underline{r}_0$, which is defined so that the activist's reputation conditional on initiated a campaign equals the unconditional reputation r_0:

$$\mathbb{P}(\mu_A = \mu_{agr}|\underline{r}_0, \mathit{13\text{-}D}) = r_0. \tag{28}$$

This is equivalent to assuming all activists receive a campaign opportunity with $\tilde{L} = 0$ on the first day they appear in the sample, meaning the initiation of a first campaign – unlike subsequent campaigns – does not affect reputation and so post-initiation reputation equals the unconditional reputation r_0.

A.2. Numeric solution and value function iteration

We solve the model numerically using value function iteration on a 106×1 grid of r_t:

$$\mathbf{r} \equiv [0, \Phi([-6, -5, -4, -3.5, -3.43, -3.36, \ldots, 3.36, 3.43, 3.5, 4]), 1], \tag{29}$$

where Φ 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 *Proxy* conditional on pre-campaign reputation r_t and choosing *13-D*, but not conditional on A's type. This formula is:

$$p_f(r_t) = \frac{r_t d_{agr}(r_t) f_{agr}(r_t) + (1-r_t) d_{caut}(r_t) f_{caut}(r_t)}{r_t d_{agr}(r_t) + (1-r_t) d_{caut}(r_t)} \tag{30}$$

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 (11), (13), and (15).

2. Find the reputation updating function both between campaigns and after campaigns. Equation (25) 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 (8) and (7) combined with Bayes' rule as follows:

$$r_{t+}|(Proxy = 1, r_t = r) = \frac{r d_{agr}(r) f_{agr}(r)}{r d_{agr}(r) f_{agr}(r) + (1-r) d_{caut}(r) f_{caut}(r)} \tag{31}$$

$$r_{t+}|(Proxy = 0, r_t = r) = \frac{r d_{agr}(r) \mathbb{P}(Settle|\mathbf{a}, r)}{r d_{agr}(r) + (1-r) d_{caut}(r)} \tag{32}$$

$$+ \frac{r d_{agr}(r)(1 - f_{agr}(r)) \mathbb{P}(Fold|\mathbf{a}, r_t)}{r d_{agr}(r)(1 - f_{agr}(r)) + (1-r) d_{caut}(r)(1 - f_{caut}(r))}. \tag{33}$$

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

$$\mathbb{P}(Settle|\mathbf{a}, r_t = r) = \frac{\mathbb{P}(\mathbf{a}|Settle, r)\mathbb{P}(Settle|r)}{\mathbb{P}(\mathbf{a}|Settle, r)\mathbb{P}(Settle|r) + \mathbb{P}(\mathbf{a}|Fold, r)\mathbb{P}(Fold|r)}, \tag{34}$$

$$\mathbb{P}(Fold|\mathbf{a}, r, = r) = 1 - \mathbb{P}(Settle|\mathbf{a}, r), \tag{35}$$

which can be computed using Equation (7) combined with equilibrium strategies.

3. Find V_i using equation:

$$\mathbf{V}_i = \mathbb{E}(\mathbf{\Pi_i}) + \delta^{1/365} \mathbf{\Sigma_i} \mathbf{V}_i, \tag{36}$$

$$\Rightarrow \mathbf{V}_i = \left(I_{106} - \delta^{1/365} \mathbf{\Sigma_i}\right)^{-1} \mathbb{E}(\mathbf{\Pi_i}) \tag{37}$$

where $\mathbf{V}_i$ is a 106×1 vector of $V_i(r_t)$ values for $r_t \in \mathbf{r}$, $\mathbb{E}(\mathbf{\Pi_i})$ is a 106×1 vector expected per-day profits for A with type i, δ is the annualized discount factor, $\mathbf{\Sigma_i}$ is a 106×106 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 (25) discretized daily, the distribution of possible observed outcomes $Proxy$ and $\mathbf{a}$ conditional on a campaign occurring (from Equation (7)), and the post-campaign reputations r_t each $\mathbf{a}$ 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 $\mathbf{r}$ 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.

- $Past\,CAR_{250}|Proxy$ is the average CAR_{250} in all the activist's prior campaigns with $Proxy = 1$, and zero if the activist has no such campaigns.

- $Past\,CAR_{250}|Hi\,Act$ is the average CAR_{250} in all the activist's prior campaigns with $Ab\,Actions$ above the full-sample median, and zero if the activist has no such campaigns.

- $Past\,CAR_{250}$ is the average CAR_{250} in all the activist's prior campaigns, and zero if the activist has no prior campaigns.

- *Prior Campaigns* is the number of previous activist campaigns initiated by the activist. This measure approximates the experience measure in Boyson et al. (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 et al. (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 et al. (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 $\widehat{Actions}$.

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

- $\widehat{Actions}$ 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.

- CAR_{250} is the market-adjusted return in days [-10,+250] 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 (38) outlines each regression:

$$a_{j,i,t+4} = \alpha_{i,t} + \gamma_{i,t} \cdot X_{j,t} + \epsilon_{j,i,t+4}, \tag{38}$$

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*$_{j,t}$.[25]

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

Appendix D. Estimation

D.1. Likelihood function details

We compute the likelihood function for each observed campaign as:

$$\mathsf{L}_c(\theta) = \mathsf{L}_c^{gap}(\theta) \cdot \mathsf{L}_c^{13-D}(\theta) \cdot \mathsf{L}_c^{car}(\theta) \cdot \mathsf{L}_c^{outcome}(\theta). \tag{39}$$

$\mathsf{L}_c^{gap}(\theta)$ 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:

$$\mathsf{L}_c^{gap}(\theta) = \sum_{s=t+1}^{t+d-1} \left[\left(1 - \frac{\lambda_c}{365}\right) + \frac{\lambda_c}{365}(r_s(1 - d_{agr}(r_s)) + (1 - r_s)(1 - d_{caut}(r_s))) \right]. \tag{40}$$

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.[26]

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

$$\mathsf{L}_c^{13-D}(\theta) = \frac{\lambda_c}{365}(r_t d_{agr}(r_t) + (1 - r_t) d_{caut}(r_t)). \tag{41}$$

$\mathsf{L}_c^{car}(\theta)$ is the probability of observed market returns CAR given pre-campaign reputation r_t and A's choice of *13-D*:

$$\mathsf{L}_c^{car}(\theta) = \phi\left(\frac{CAR - \mathbb{P}(\textit{Settle} \text{ or } \textit{Fight}|r_t, \textit{13-D})}{\sigma_{car}}\right), \tag{42}$$

$$\mathbb{P}(\textit{Settle} \text{ or } \textit{Fight}|r_t, \textit{13-D}) = y(r_t) + (1 - y(r_t)p_f(r_t), \tag{43}$$

where ϕ is the PDF of the standard normal distribution.

Finally, $\mathsf{L}_c^{outcome}(\theta)$ is the probability of observed outcome $\mathbf{o}$ given pre-campaign reputation r_t and A's choice of *13-D*:

$$\mathsf{L}_c^{outcome}(\theta) = \begin{cases} (1 - y(r_t))p_f(r_t) & \text{if } Proxy = 1 \\ y(r_t)\mathbb{P}(\mathbf{a}|\textit{Settle}) + (1 - y(r_t))(1 - p_f(r_t))\mathbb{P}(\mathbf{a}|\textit{Fold}) & \text{if } Proxy = 0 \end{cases} \tag{44}$$

[25] We define in detail how we calculate each of the actions and characteristics in Appendix B.

[26] 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.

D.2. Mapping between μ and zero-reputation probabilities

To ease the interpretation of our model's parameters, we map means of log costs μ_L, μ_M, μ_{agr}, and μ_{caut} to what they imply for strategies when reputation equals zero. This mapping is:

$$f_{caut,0} = \Phi\left(\tau_A(\log(\Delta) - \mu_{caut})\right), \tag{45}$$

$$f_{agr,0} = \Phi\left(\tau_A(\log(\Delta) - \mu_{agr})\right), \tag{46}$$

$$y_0 = 1 - \Phi\left(\tau_M\left(\log\left(\frac{1 - f_{caut,0}}{f_{caut,0}}\right) - \mu_M\right)\right), \tag{47}$$

$$d_{caut,0} = \Phi\left(\tau_L(\log(\overline{L}_{caut,0}) - \mu_L)\right), \tag{48}$$

$$\overline{L}_{caut,0} = y_0\Delta + (1 - y_0)f_{caut,0}\left(\Delta - \mathbb{E}\left[\tilde{F}_A \mid \tilde{F}_A < \Delta, \mu_A = \mu_{caut}\right]\right). \tag{49}$$

D.3. Simulating samples

Our analyses in Tables 6 and 7 use samples simulated from the model. For a given parameterization of the model θ, 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., and has reputation conditional on filing a *13-D* equal to r_0.

2. Draw random type reset dates according to rate λ_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 λ_c.

4. Starting with the first campaign at t_0, randomly draw costs $\tilde{L}$, $\tilde{F}_M$, and $\tilde{F}_A$ and compute the resulting campaign outcome. From this outcome, draw random $\mathbf{a}$ using Equation (7). Then compute post-campaign reputation r_{t+} and, based on Equation (25), 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.

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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. For *Settle* and *Fold* outcomes, we plot expected r_{t+} across possible realizations of $\mathbf{a}$. All five plots are a function of pre-campaign reputation r_t for the dynamic equilibrium and unconditional reputation r_0 for the static equilibrium. Subscripts *agr* and *caut* indicate strategies for aggressive and cautious activists, respectively.

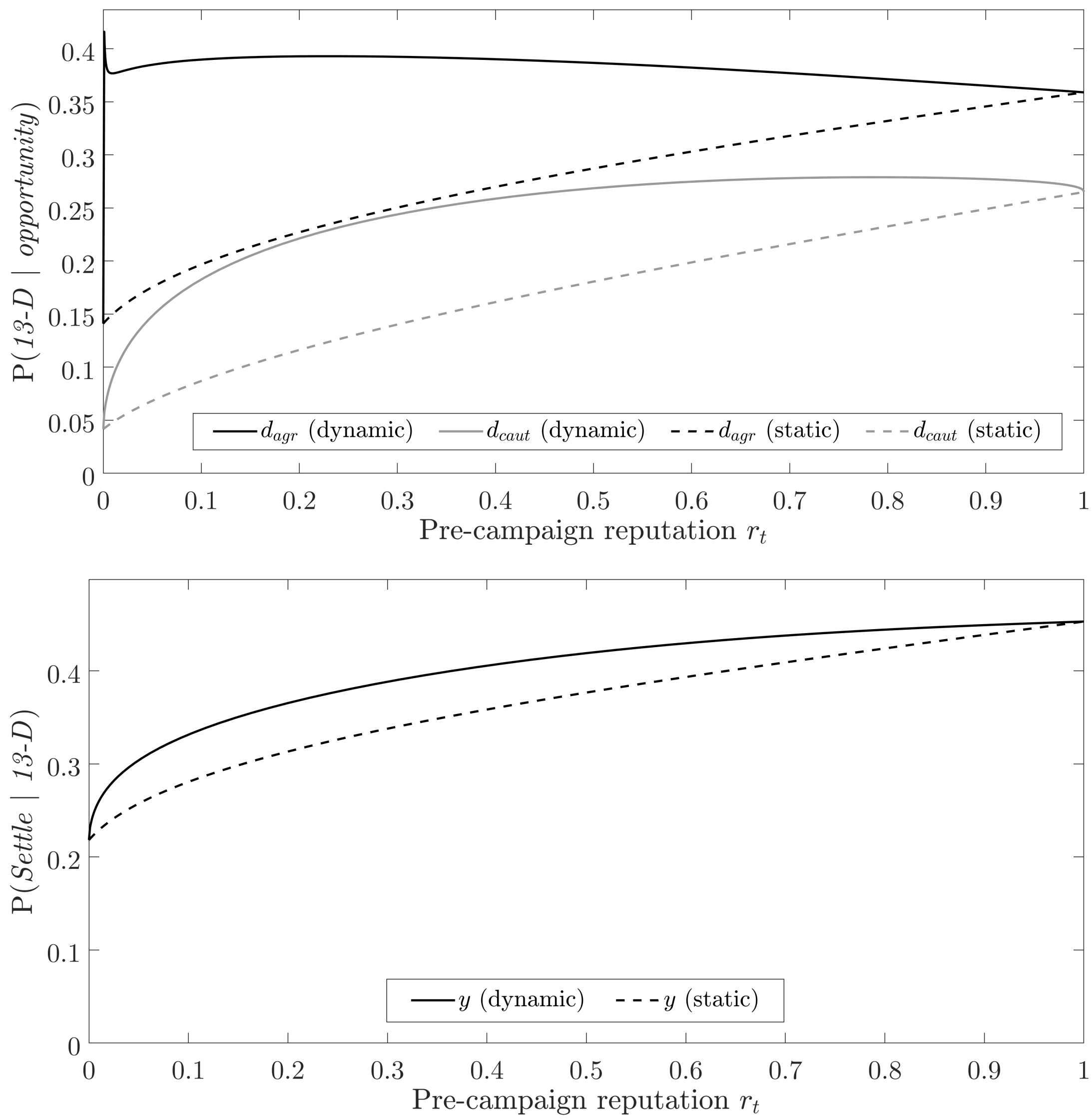
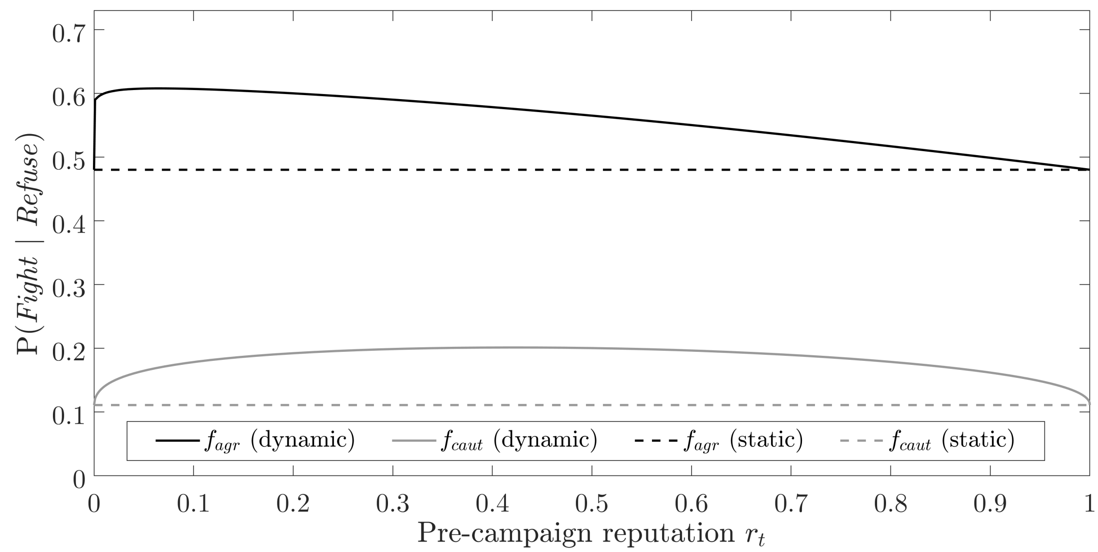
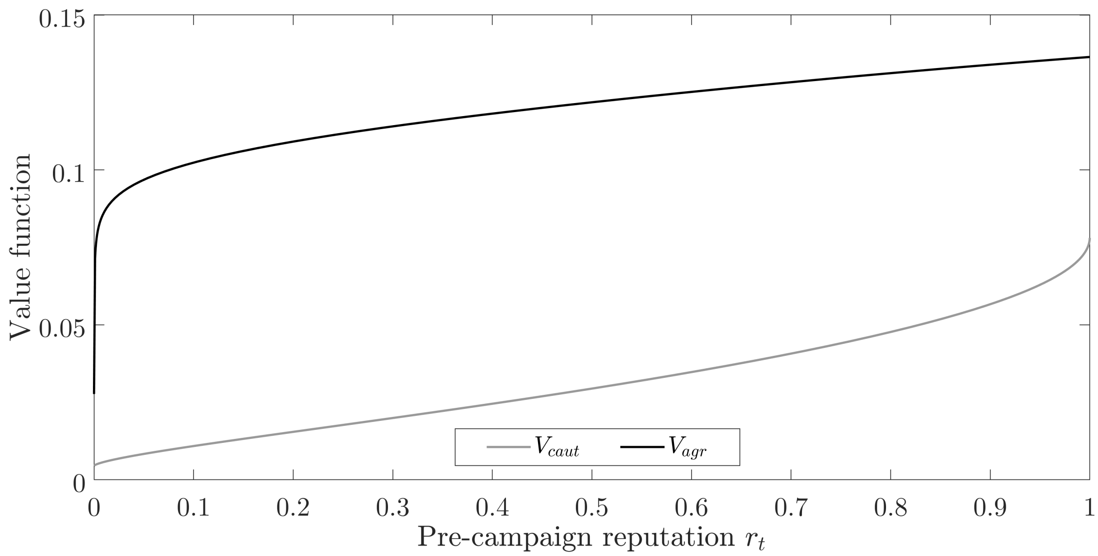


Fig. 1 (cont'd): Estimated Equilibrium





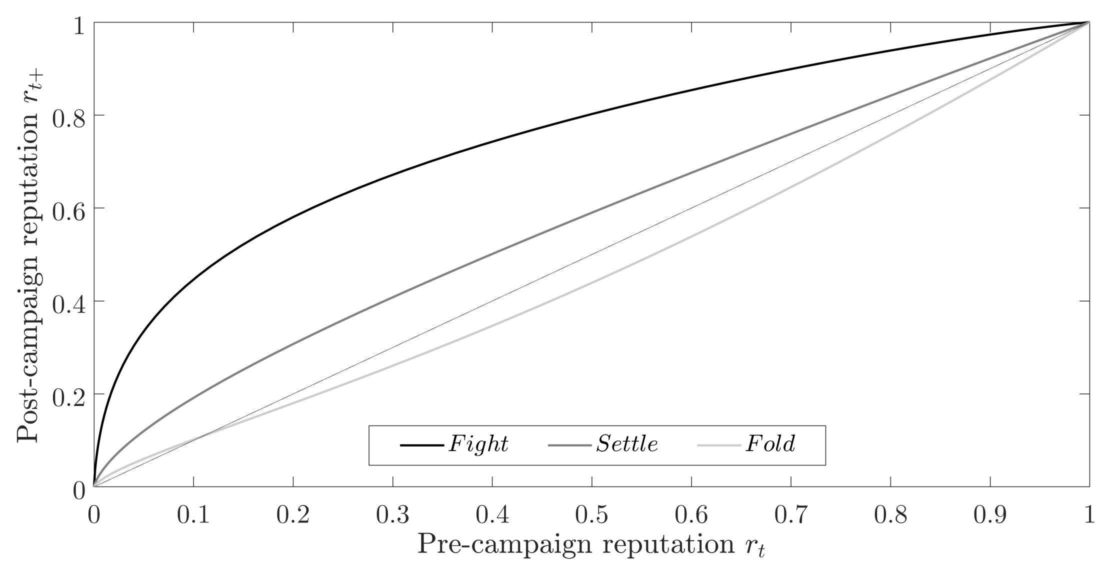
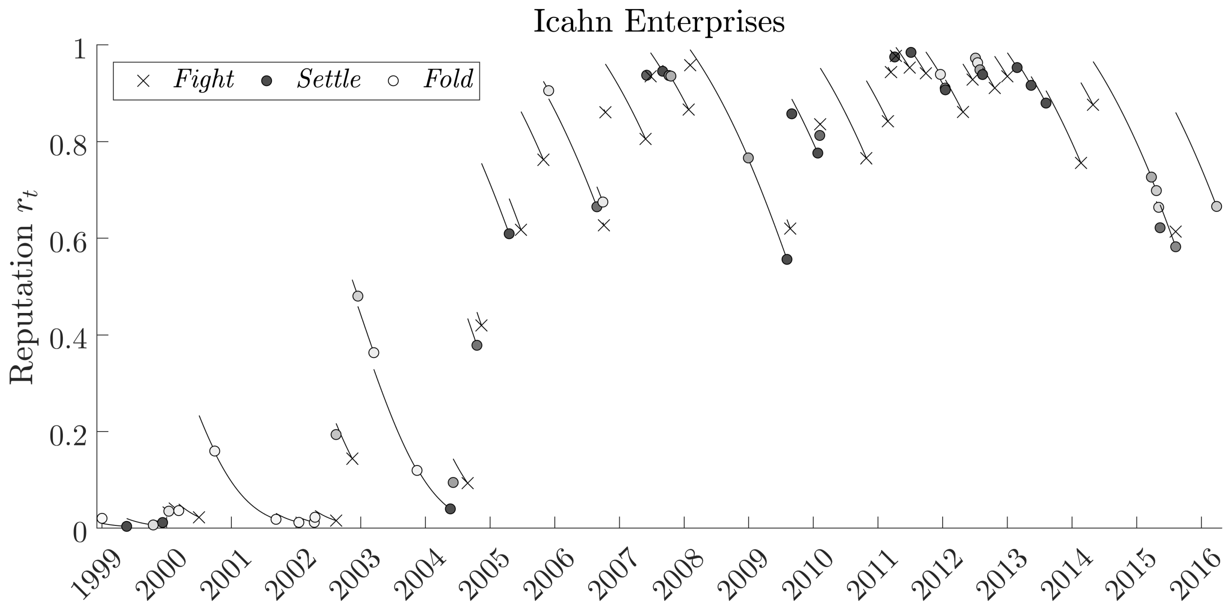


Figure 2: Example Reputation Dynamics

We plot the time series of model-implied 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.



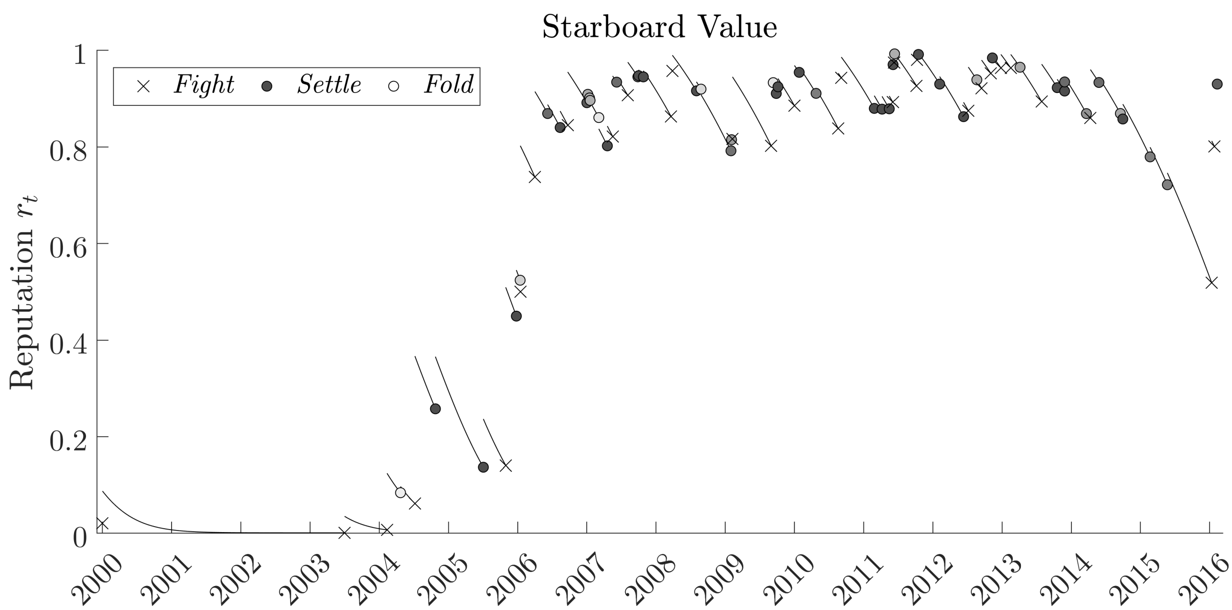
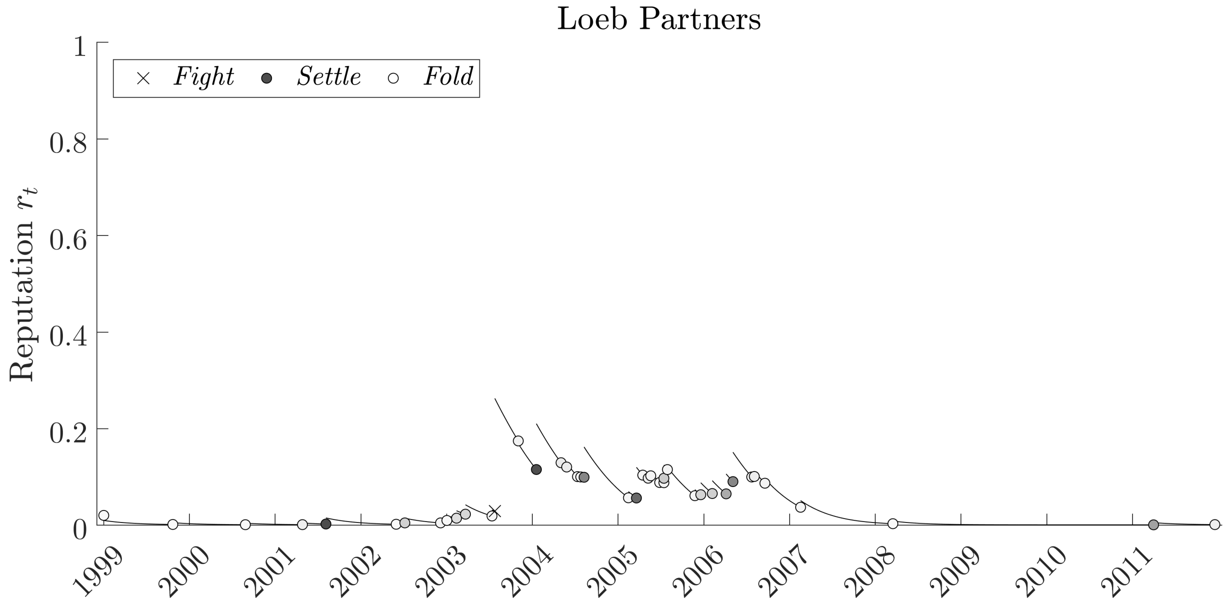


Fig. 2: Example Reputation Dynamics (cont'd)



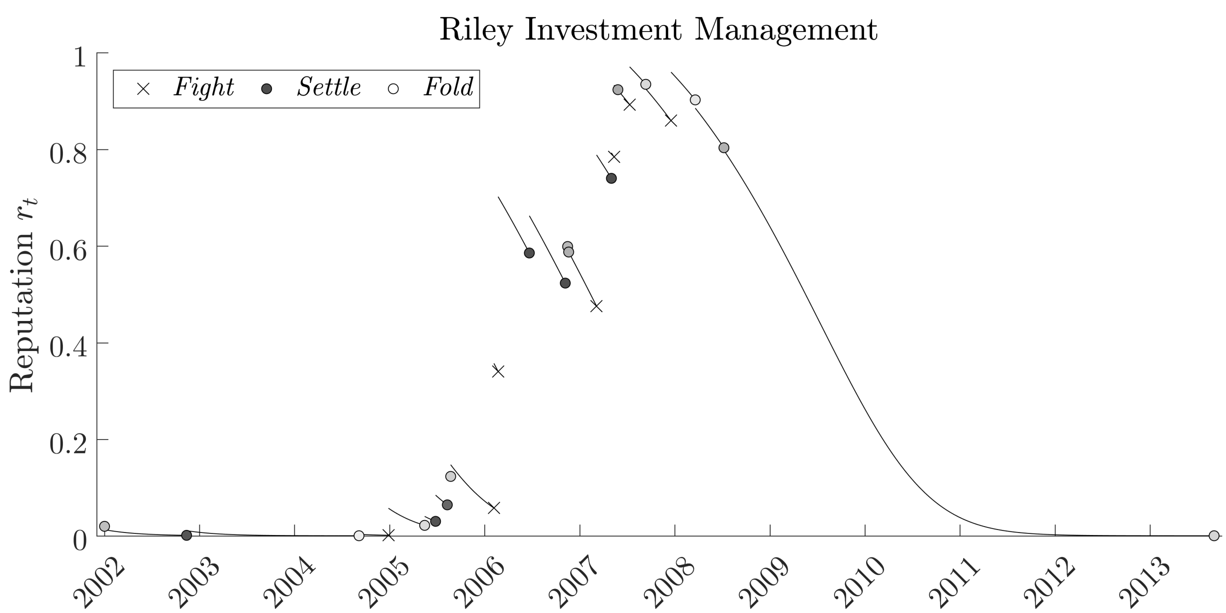


Figure 3: Comparative Statics

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

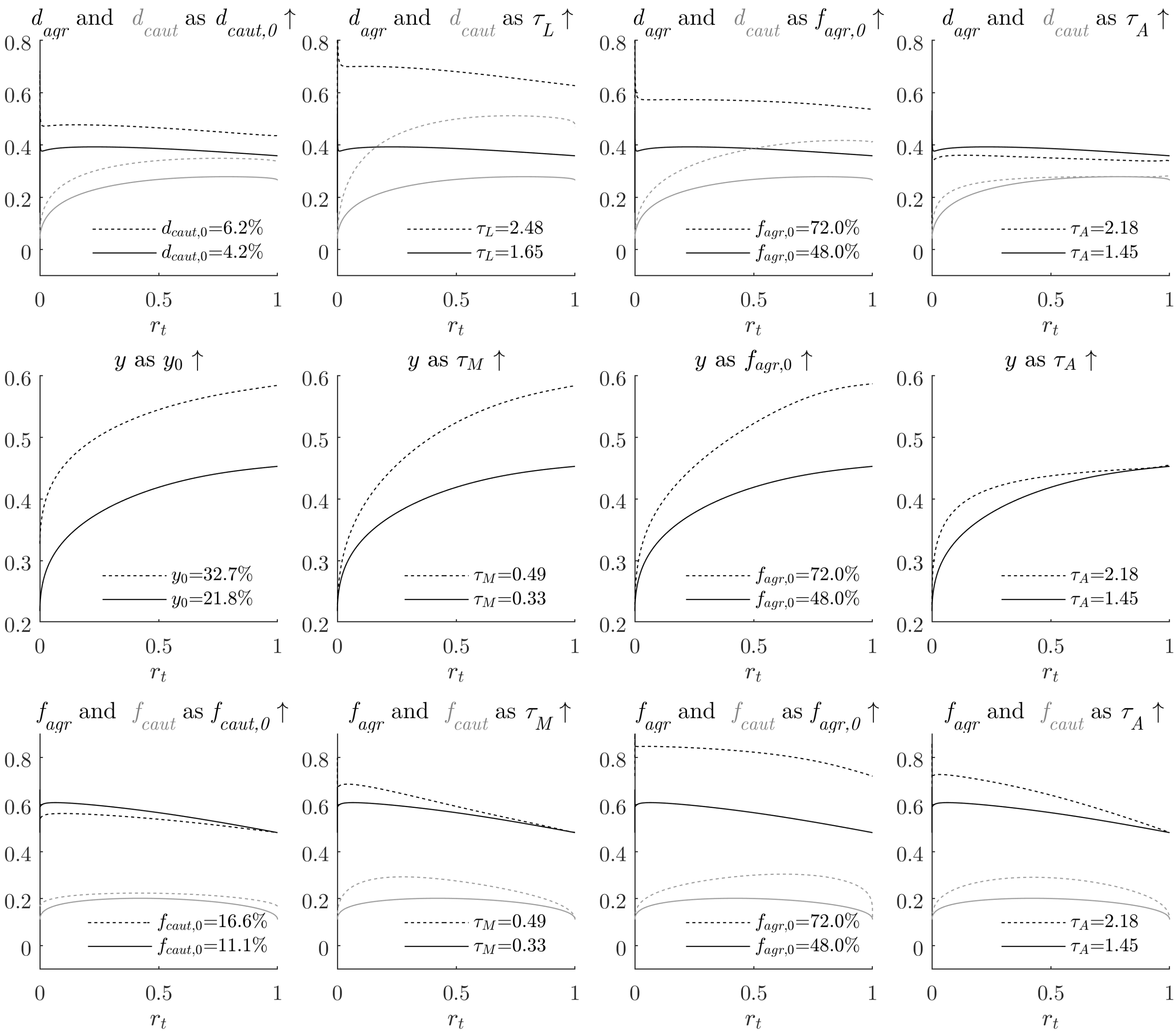


Figure 4: Model Identification

We show how different parameterizations affect model-predicted observable outcomes as a function of activist reputation r_t. The outcomes are *13-D*/yr, the annualized rate at which an activist initiates a campaigns; $P(Settle)$, the percent probability a campaign is settled; $P(Fight)$, the percent probability a campaign ends in a proxy fight; $(r_{t+} - r_t)|Settle$, the increase in r_t after a campaign ending in *Settle*; and $(r_{t+} - r_t)|Fight$, the increase in r_t after a campaign ending in *Fight*. The solid line in each plot represents the baseline functional form in our model with estimated parameters presented in Table 2, while the dotted line presents the equilibrium functional form when a single parameter is increased by 50%.

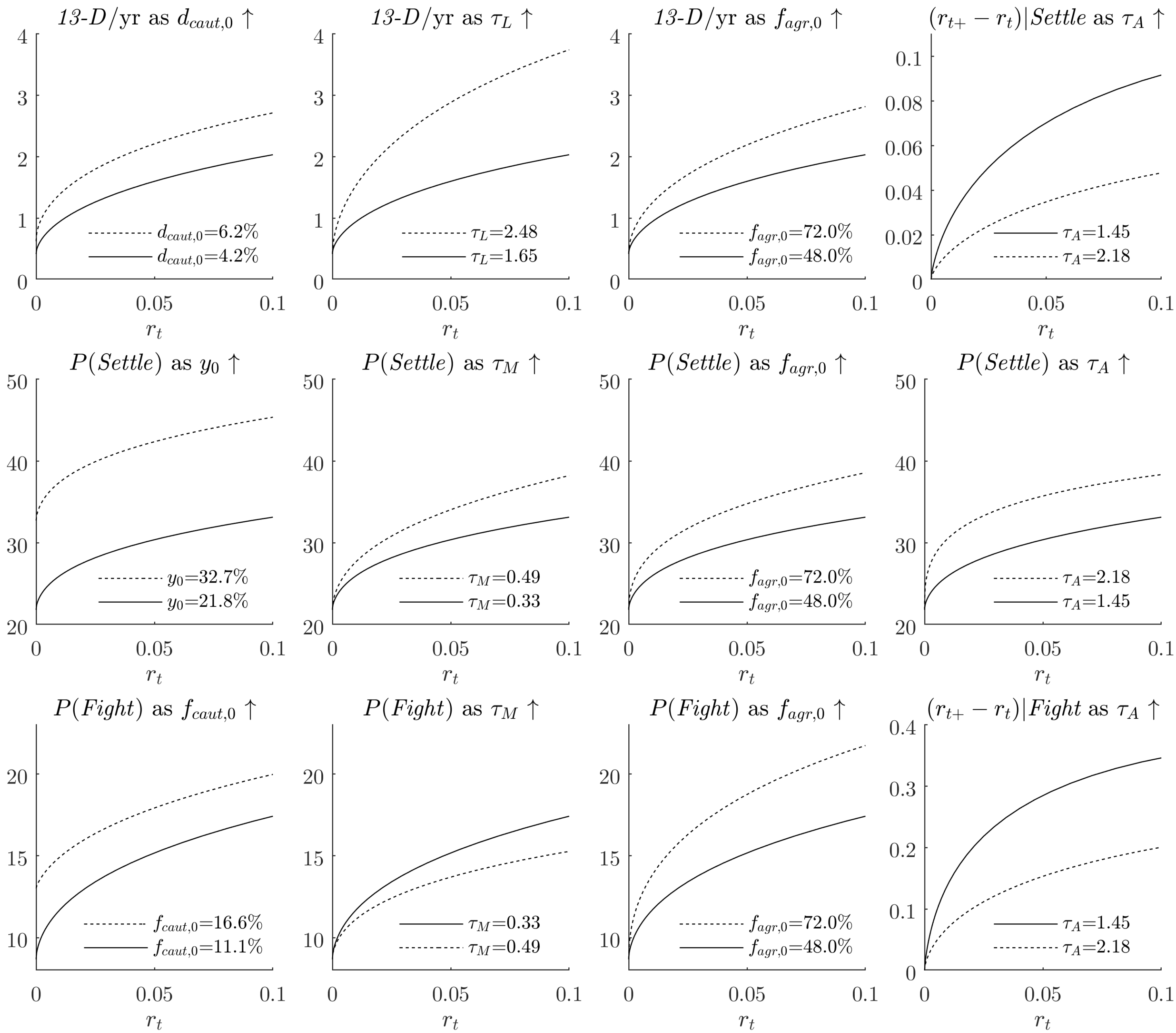


Table 1: Descriptive Statistics

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, $\widehat{Action}$ is its expected value in the absence of activism based on the regressions discussed in Appendix C and *Ab Action* is $Action - \widehat{Action}$. *Actions* is the sum of these five indicators, $\widehat{Actions}$ is the sum of the $\widehat{Action}$, and *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.

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

Table 2: Estimated Model Parameters and Hypothesis Tests

Panel A describes the model parameters we estimate and gives their estimated values. We also provide standard errors accounting for estimation error in σ_{car} and β and 95% confidence intervals based on likelihood ratio tests, both detailed in Online Appendix C. Panel B describes the model parameters we fix 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 χ^2 statistic and its p-value. Our sample consists of 2,434 campaigns initiated by hedge funds during 1999–2016.

Panel A: Parameters estimated using maximum likelihood

Param.	Description	Estimate	SE	95% C.I.
Δ	Value of project A demands / market cap (%)	6.62	(0.66)	[5.70, 7.35]
$d_{caut,0}$	Prob. cautious A chooses *13-D* given $r_{t-} = 0$ (%)	4.16	(0.63)	[2.78, 8.83]
τ_L	Precision log(Cost of campaign to A)	1.65	(0.19)	[0.48, 2.06]
y_0	Prob. M settles given $r_{t-} = 0$ (%)	21.82	(2.43)	[12.87, 24.22]
τ_M	Precision log(M proxy fight cost/M project cost)	0.33	(0.15)	[0.11, 0.48]
$f_{caut,0}$	Prob cautious A chooses *fight* given $r_{t-} = 0$ (%)	11.10	(2.81)	[2.44, 14.66]
$f_{agr,0}$	Prob aggressive A chooses *fight* given $r_{t-} = 0$ (%)	48.03	(6.66)	[40.73, 60.38]
τ_A	Precision log(A proxy fight cost)	1.45	(0.64)	[0.72, 2.42]
r_0	Unconditional prob. A is aggressive (%)	2.05	(1.94)	[1.00, 9.80]
λ_r	Arrival rate of type resets (annualized)	0.19	(0.07)	[0.08, 0.36]

Panel B: Parameters assumed or directly estimated

Param.	Description	Value
δ	Activists' annual discount factor	0.90
σ_{car}	Standard dev. of camp. announcement 3-day CAR (%)	8.99
β_{reorg}	Added prob. of reorganization in successful camp. (%)	32.25
β_{payout}	Added prob. of payout increase in successful camp. (%)	6.16
β_{ceo}	Added prob. of CEO change in successful camp. (%)	17.53
β_{board}	Added prob. of board change in successful camp. (%)	67.63
β_{acq}	Added prob. of M&A activity in successful camp. (%)	30.76
λ_c	Arrival rate of camp. opportunities (annualized)	10.00

Panel C: Hypothesis tests

Model	Δ	$d_{caut,0}$	τ_L	y_0	τ_M	$f_{caut,0}$	$f_{agr,0}$	τ_A	r_0	λ_r	χ^2	p-value
Baseline	6.62	4.16	1.65	21.82	0.33	11.10	48.03	1.45	2.05	0.19		
No reputation	6.67	9.94	–	28.05	–	19.87	–	–	–	–	340.1	0.00%
Full information	6.80	9.12	2.00	29.52	0.12	12.36	64.15	–	0.85	–	21.0	0.00%

Table 3: Moments and Identification

We present model predictions and observed values of four different outcome variables, all defined in Table 1. We present average values for these moments in the full sample as well as four subsample differences: high r_t observations (those with $r_t > 50\%$) minus low r_t observations (those with $r_t < 0.5\%$); observations with recently updated r_t (those where A has five or more campaigns and an increase in r_t over the prior year) minus the full sample; observations with new A (those where A's first campaign was in the prior year) minus the full sample; and observations with decaying r_t (those with $r_t > r_0$ and over a year since the prior campaign) minus the full sample. For each moment and subsample, we present average observed values in the data; standard errors for data averages clustered by activist; average predicted values in our baseline model, no-reputation, and full-information models; and local elasticities of our baseline model's prediction for each moment to changes in each of models parameters. We only tabulate elasticities larger than 0.25 in absolute value. Elasticities highlighted in grey are the focus of our discussion in Section 3.6. $^{\uparrow}$, $^{\uparrow\uparrow}$ and $^{\uparrow\uparrow\uparrow}$ ($^{\downarrow}$, $^{\downarrow\downarrow}$ and $^{\downarrow\downarrow\downarrow}$) indicate the alternative model fits the data moment significantly better (worse) than the baseline model with p-values below 10%, 5%, and 1%, respectively. The 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.

	Data:		Model-estimated value:			Elasticity with respect to:									
Moment:	Value	S.E.	Baseline	No rep.	Full info.	Δ	$d_{caut,0}$	τ_L	y_0	τ_M	$f_{caut,0}$	$f_{agr,0}$	τ_A	r_0	λ_r
Full sample															
Mean *CAR*	2.82	(0.25)	2.80	2.82	2.90	1.00			0.54						
Mean *13-D*	1.00	(0.08)	0.93	1.06	1.08		0.45	0.44			−0.25				
Mean $Ab\ Actions \mid Proxy = 0$	0.65	(0.04)	0.52	0.51	0.55				0.86						
Mean *Proxy*	14.30	(1.67)	13.74	14.30	11.87				−0.28	−0.27	0.66				
Observations with high r_t − Observations with low r_t															
Mean *13-D*	2.93	(0.24)	2.86	$0.00^{\downarrow\downarrow\downarrow}$	$2.21^{\downarrow\downarrow\downarrow}$		0.39	1.60	−0.86	0.66	−0.62	1.15			
Mean $Ab\ Actions \mid Proxy = 0$	0.37	(0.17)	0.50	0.00	0.36					0.60	−0.42	1.16			
Mean *Proxy*	25.25	(3.63)	15.43	$0.00^{\downarrow\downarrow}$	20.43				−0.66	−0.78		0.79			
Observations with recently-updated r_t − All observations															
Mean *13-D*	3.87	(0.51)	1.59	$0.00^{\downarrow\downarrow\downarrow}$	0.77			1.60	−0.89	0.35	−0.34	0.51	−0.36		
Mean $Ab\ Actions \mid Proxy = 0$	−0.02	(0.11)	0.21	$0.00^{\uparrow}$	0.08					0.32		0.58	−0.26		
Mean *Proxy*	1.74	(3.63)	6.70	0.00	4.40				−0.76	−0.99		0.31	−0.28		
Observations with New A − All observations															
Mean *13-D*	−0.57	(0.11)	−0.21	$0.00^{\downarrow}$	−0.12		0.30	−0.57		−0.26			0.31		
Mean $Ab\ Actions \mid Proxy = 0$	0.06	(0.08)	−0.07	0.00	−0.03		0.64	1.03	−0.78	−0.25			0.27	0.42	
Mean *Proxy*	−1.43	(2.20)	−2.11	0.00	−1.94		0.66	1.05		1.11	−0.35	0.46	0.31	0.35	
Observations with decaying r_t − All observations															
Mean *13-D*	1.00	(0.59)	1.25	0.00	0.77		−0.30	−0.86	0.87	0.38	−0.46	−0.91			−0.56
Mean $Ab\ Actions \mid Proxy = 0$	0.14	(0.45)	0.15	0.00	0.05		−0.72	−2.81	2.15	0.61	−0.59	−0.53	0.44		−0.54
Mean *Proxy*	23.80	(9.56)	5.14	0.00	2.88		−0.69	−2.69	1.23	−0.67		−0.64	0.38		−0.49

Table 4: 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

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

Panel B: Highest reputation activists

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

Table 5: 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

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

Panel B: Campaigns sorted by r_t

r_t (%) range:	All	[0, 0.5]	[0.5, 5]	[5, 50]	[50, 100]
% of campaigns	100.00	48.81	22.51	19.76	8.92
		Strategies			
y (% of *13-D*)	28.55	23.86	26.97	34.89	44.11
f_{caut} (% of *Refuse*)	14.62	12.61	14.54	18.41	17.45
f_{agr} (% of *Refuse*)	58.98	59.26	60.19	60.07	51.96
		Outcomes			
Ab Actions (model)	0.65	0.52	0.61	0.83	1.08
Ab Actions (data)	0.78	0.73	0.69	0.77	1.24
Ab Actions$\mid Proxy = 0$ (model)	0.51	0.41	0.48	0.66	0.91
Ab Actions$\mid Proxy = 0$ (data)	0.65	0.63	0.58	0.66	1.00
CAR (model) (%)	2.80	2.25	2.61	3.55	4.61
CAR (data) (%)	2.82	2.78	2.53	2.45	4.59
$Proxy$ (model) (%)	13.74	10.12	12.46	18.79	25.55
$Proxy$ (data) (%)	14.30	11.62	10.22	15.38	36.87
		Motivations			
Short-term profitable (% of *Fight*)	81.17	87.95	76.62	68.77	90.16
Reputation building (% of *Fight*)	18.83	12.05	23.38	31.23	9.84

Table 6: Reputation and Activist Campaign Outcomes

We present panel regressions using our model-based reputation measure r_t to predict four dependent variables: *13-D*, an indicator for whether there is a campaign initiation on a given activist-day; *Ab Actions*, the total number of abnormal activism-related corporate actions by target firms in the year following campaign initiation; CAR, the target's [-1,1] market-adjusted return around the campaign initiation date; $Proxy$, an indicator for whether the campaign features a proxy fight. In Column (3) we predict *Ab Actions* in the subsample of campaigns with $Proxy = 0$. Panel A does not include activist fixed effects, while Panel B does. Both Panels A and B show average coefficients from the same regressions in samples simulated using the model under three null hypotheses: the full model, the no-reputation alternative model, and the full-information alternative model, all parameterized using the values in Table 2. In Panel C 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. For each null, *** indicates we reject at 1% level, ** indicates 5%, and * indicates 10%.

Panel A: Main Regressions

	(1) *13-D*	(2) *Ab Actions*	(3) *Ab Actions* $\|Proxy = 0$	(4) CAR	(5) $Proxy$
Data Coefficient	4.43	0.71	0.55	2.60	34.26
Standard error	(0.53)	(0.18)	(0.18)	(0.70)	(4.32)
Sim. Coefficient (model null)	4.19	0.77	0.72	3.53	19.88***
Sim. Coefficient (no rep. null)	−0.02***	−0.07***	−0.03***	0.04***	−4.10***
Sim. Coefficient (full info. null)	3.39**	0.72	0.59	3.25	33.08

Panel B: Activist Fixed Effects

	(1) *13-D*	(2) *Ab Actions*	(3) *Ab Actions* $\|Proxy = 0$	(4) CAR	(5) $Proxy$
Data Coefficient	1.59	−0.06	−0.06	0.88	7.86
Standard error	(0.38)	(0.17)	(0.20)	(1.19)	(6.62)
Sim. Coefficient (model null)	2.13	−0.08	0.26	3.20*	−0.33
Sim. Coefficient (no rep. null)	−3.05***	−1.52***	−0.58***	0.03	−1.03
Sim. Coefficient (full info. null)	−2.64***	−0.45**	−0.27	0.02	−0.31

Table 6: [Continued] Reputation and Activist Campaign Outcomes

Panel C: Robustness

	(1)	(2)	(3)	(4)	(5)
	13-D	*Ab Actions*	*Ab Actions* $\|Proxy = 0$	*CAR*	*Proxy*
r_t	2.82***	0.93***	0.74***	2.91**	40.04***
	(0.73)	(0.23)	(0.25)	(1.22)	(8.42)
$Past\, CAR_{250} \| Proxy$	0.06	−0.16	−0.09	−0.41	0.06
	(0.14)	(0.18)	(0.19)	(0.80)	(5.56)
$Past\, CAR_{250} \| Hi\ Act$	0.14	0.03	0.00	0.73	4.71
	(0.16)	(0.17)	(0.16)	(1.13)	(4.58)
$Past\, CAR_{250}$	−0.01	−0.24	−0.24	−0.05	0.83
	(0.12)	(0.17)	(0.17)	(1.25)	(3.77)
Log Portfolio Size	0.01	0.00	0.00	0.04	−2.85***
	(0.02)	(0.03)	(0.03)	(0.16)	(0.77)
Portfolio Turnover	−0.20**	−0.12	−0.08	−0.02	−1.54
	(0.08)	(0.07)	(0.08)	(0.51)	(2.35)
Number of Prior Campaigns	0.06***	0.00	0.00	−0.01	−0.08
	(0.01)	(0.00)	(0.00)	(0.02)	(0.08)
Stake Size		−0.69	−0.08	0.43	−49.70***
		(0.54)	(0.54)	(3.94)	(18.49)
Top Investor Hedge Fund	0.02	0.10	0.14	−0.13	3.80
	(0.13)	(0.09)	(0.10)	(0.64)	(2.34)

Table 7: Counterfactuals

We present 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 25,000 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.

		Counterfactual		
	Baseline	No reputation	No aggressive A	Full information
		Pre-opportunity reputation r_t (%)		
Cautious A	1.21	2.05	0.00	0.00
Aggressive A	40.29	2.05	–	100.00
All	2.00	2.05	0.00	2.05
		13-D (% of opportunities)		
Cautious A	8.73	5.43	4.16	4.16
Aggressive A	38.62	15.82	–	35.89
All	9.34	5.65	4.16	4.81
		Settle (% of campaigns)		
Cautious A	26.50	23.81	21.82	21.82
Aggressive A	37.65	23.81	–	45.31
All	27.44	23.81	21.82	22.31
		Fight (% of refusals)		
Cautious A	13.82	11.10	11.10	11.10
Aggressive A	55.74	48.03	–	48.03
All	16.85	11.86	11.10	11.86
		Target shareholders' average payoff (bp per opportunity)		
Cautious A	21.19	11.60	8.41	8.41
Aggressive A	185.11	63.28	–	170.05
All	24.53	12.67	8.41	11.73
		Activists' average net payoff (bp per opportunity)		
Cautious A	2.62	1.94	1.33	1.33
Aggressive A	23.26	9.71	–	39.87
All	3.04	2.10	1.33	2.12