



# Reputation and investor activism: A structural approach<sup>☆</sup>

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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 that activism adds for target shareholders.

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## 1. Introduction

Activists capture only 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 (Bebchuk et al., 2020; Brav et al., 2008, 2010). 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 instead of risking 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

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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 fourth 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 paying only 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 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. For example,

activist investor Carl Icahn said, "I enjoy the hunt much more than the 'good life' after the victory."

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 2434 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 Securities and Exchange Commission (SEC) filings, SharkWatch, and the Center for Research in Securities Prices (CRSP). Our model also yields predictions for the likelihood of settlements, which we infer from target firm reorganizations, payout increases, chief executive officer (CEO) changes, board changes, and mergers and acquisitions (M&A) observed in Compustat and Capital IQ.<sup>1</sup> 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.<sup>2</sup>

Using our estimated model parameters, we quantify reputation's role in each stage of our activism game. In the first stage, we find high reputation activists initiate 3.5 campaigns per year, compared to only 0.6 for low reputation activists.<sup>3</sup> 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 (i.i.d.) outcomes. We find that this

<sup>1</sup> 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., 2020](#)) to estimate whether a specific campaign was settled using data from multiple sources.

<sup>2</sup> Our estimated reputation measure for campaigns in our sample are available on Travis Johnson's website (<http://travislakejohnson.com>).

<sup>3</sup> For these statistics, a low reputation activist has probability less than 0.5% of being the aggressive type and a high reputation activist has probability above 50%.

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 i.i.d. A potential alternative explanation for the non-i.i.d. 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 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 while three-day target returns around campaign announcements are somewhat less sensitive to reputation than our model predicts, 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; Back et al., 2018). In this literature, large shareholders are effective activists because their position sizes reduce the free rider problem. Levit (2018) extends the literature by examining communication and exit as alternate channels to avoid costly proxy fights. 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.<sup>4</sup> 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 that activists with more experience produce larger announcement returns and better long-term target performance.

Bebchuk et al. (2020) 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.

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 differ in important

<sup>4</sup> 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).

ways. Gantchev (2013) estimates a statistical sequential decision model featuring a single campaign. 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 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

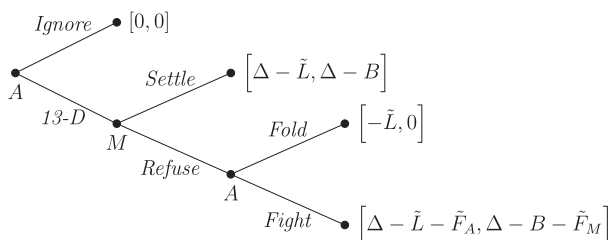
Our model adapts the canonical reputation framework with one long-lived player of unknown type and many short-lived players to investor activism. This framework originated in Kreps and Wilson (1982) and Milgrom and Roberts (1982), which study the chain-store stage game, and was generalized to other stage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

$M$  controls a firm with access to a project that would generate an average return for shareholders of  $\Delta > 0$ .  $M$  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  $\Delta$  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 that 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



**Model Fig. 1.** Stage game tree. Each stage game takes the form depicted by this figure. Nodes marked with  $A$  are decisions made by the activist, nodes marked with  $M$  are decisions made by the target manager. Payoffs for the activist and manager are presented in brackets for each possible outcome.

gets a payoff of zero. 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. Prior to a proxy fight,  $M$  decides whether to refuse  $A$ 's demands (Refuse) or settle (Settle), in which case they undertake the project and the game ends, making the payoffs

$$[\Pi_{A, \text{Settle}}, \Pi_{M, \text{Settle}}] = [\Delta - \tilde{L}, \Delta - B]. \quad (1)$$

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  $\Delta$ .<sup>5</sup> 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 (Bebchuk et al., 2020; Fos and Tsoutsoura, 2014; Gow et al., 2014). Therefore, if  $A$  chooses Fight, the payoffs are

$$[\Pi_{A, \text{Fight}}, \Pi_{M, \text{Fight}}] = [\Delta - \tilde{L} - \tilde{F}_A, \Delta - B - \tilde{F}_M]. \quad (2)$$

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

$$[\Pi_{A, \text{Fold}}, \Pi_{M, \text{Fold}}] = [-\tilde{L}, 0]. \quad (3)$$

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

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

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

$$\text{and } \log(\tilde{F}_A) \sim N(\mu_A, \tau_A^{-2}). \quad (6)$$

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



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

Activists differ only by their  $\mu_A$ , which takes one of two values:  $\mu_{agr} < \mu_{caut}$ .<sup>6</sup> When  $A$  has  $\mu_A = \mu_{agr}$ , they are more likely to fight and we therefore refer to them as the aggressive type; when  $A$  has  $\mu_A = \mu_{caut}$ , we refer to them as the cautious type. Aggressive  $A$  could 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 choose *Settle*.  $A$  knows the distribution of  $\tilde{F}_M$  but not its realization. Similarly,  $M$  only knows the distribution of  $\tilde{L}$  and  $\tilde{F}_A$ . All other parameters, including  $\Delta$  and  $B$ , are common knowledge and fixed across campaigns.<sup>7</sup>

### 3.2. Dynamics

Campaign opportunities arrive exogenously according to a Poisson process with an annualized arrival rate  $\lambda_c$ , which we assume is the same for all activists.<sup>8</sup> Upon receiving a campaign opportunity, the above stage game is played instantly. When playing each stage game,  $A$  maximizes their expected payoffs across the current and all future campaign opportunities, using an annual discount factor  $\delta$ . Each  $M$  is targeted only 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 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 see 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 assume that  $M$  can observe the true outcomes of past activist campaigns, true

<sup>6</sup> Another possible difference between types of activists is in their idea quality, which would result in  $\Delta$  varying across activists. 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 that  $\Delta$  does not vary substantially across activists.

<sup>7</sup> In Online Appendix E, we show that allowing  $\Delta$  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.

<sup>8</sup> 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.

**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. Dashes indicate the outcome is not observed. True outcomes can be no campaign opportunity (*No opportunity*), or a campaign opportunity that ends with *Ignore*, *Fold*, *Settle*, or *Fight*, as described in Section 3.1.

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

$r_t$  would become unobservable to us as econometricians and we would need to estimate an evolving distribution of possible  $r_t$  for each  $A$  instead of 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.

$M$  faces two main data limitations, summarized by Model Table 1 and motivated empirically in Section 4.1. First, they do not observe campaign opportunities  $A$  chooses to ignore, instead only observing an indicator (*13-D*) that 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*. Second, 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  $\Delta$  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:

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

where  $a_i$  is the  $i$ th action in vector  $\mathbf{a}$ ,  $\hat{a}_i$  is its predicted value in the absence of activism, and  $\beta_i$  is the added probability of action  $i$  during a campaign ending in *Settle* or *Fight*. We detail the  $a_i$  we use in Section 4.1, and our calibration of  $\hat{a}_i$  and  $\beta_i$  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,  $A$ 's reputation updates to the posterior  $r_{t+}$ :

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

Between campaigns,  $r_t$  evolves continuously for two reasons. First, the absence of campaigns indicates that a campaign opportunity could have arrived but  $A$  chose *Ignore*. Because a cautious  $A$  is more likely to choose *Ignore*,  $r_t$  decays with each passing moment as it is increasingly likely

A ignored an opportunity. Second, a chance exists that A will have a change in fund management or investment strategy that results in their type being re-drawn from the unconditional distribution. These type resets arrive according to a Poisson process with an annualized arrival rate  $\lambda_r$  and are observed by A but not by M. We include them in our model because they cause  $r_t$  to revert toward  $r_0$ , allowing learning in the model to continue indefinitely instead of  $r_t$  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.<sup>9</sup> See Appendix A for the relevant formulas.

Because A knows that  $r_t$  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

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

and  $\mathbb{E}(\Pi_i(r_{t+s}) | r_t = r, \mu_A = \mu_i)$  is the expected payoff to an A of type  $i$  for 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 A 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 choose 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  $\tilde{F}_A$ :

$$\tilde{F}_A \leq \Delta + V_i(r_{t+} | \text{Fight}) - \mathbb{E}[V_i(r_{t+}) | \text{Fold}] \equiv \bar{F}_i, \quad (10)$$

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. No uncertainty exists 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

$$f_i(r_t) = \Phi(\tau_A^{-1}(\log(\bar{F}_i) - \mu_i)), \quad (11)$$

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:

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

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 that 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  $\mu_M$  and  $\tau_M$ , but have no way of separating  $\tilde{F}_M$  and  $B - \Delta$ . Eq. (12) implies M's probability of settling satisfies

$$y(r_t) = 1 - \Phi(\tau_M^{-1}(\log(\bar{F}_M) - \mu_M)). \quad (13)$$

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

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

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

$$d_i(r_t) = \Phi(\tau_L^{-1}(\log(\bar{L}_i) - \mu_L)). \quad (15)$$

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

We consider, as a benchmark for testing hypotheses and evaluating counterfactuals, 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  $f_i^s$  for the equilibrium strategies in a one-shot stage game, we simplify the cutoff values  $\bar{L}_i$  and  $\bar{F}_i$  to

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

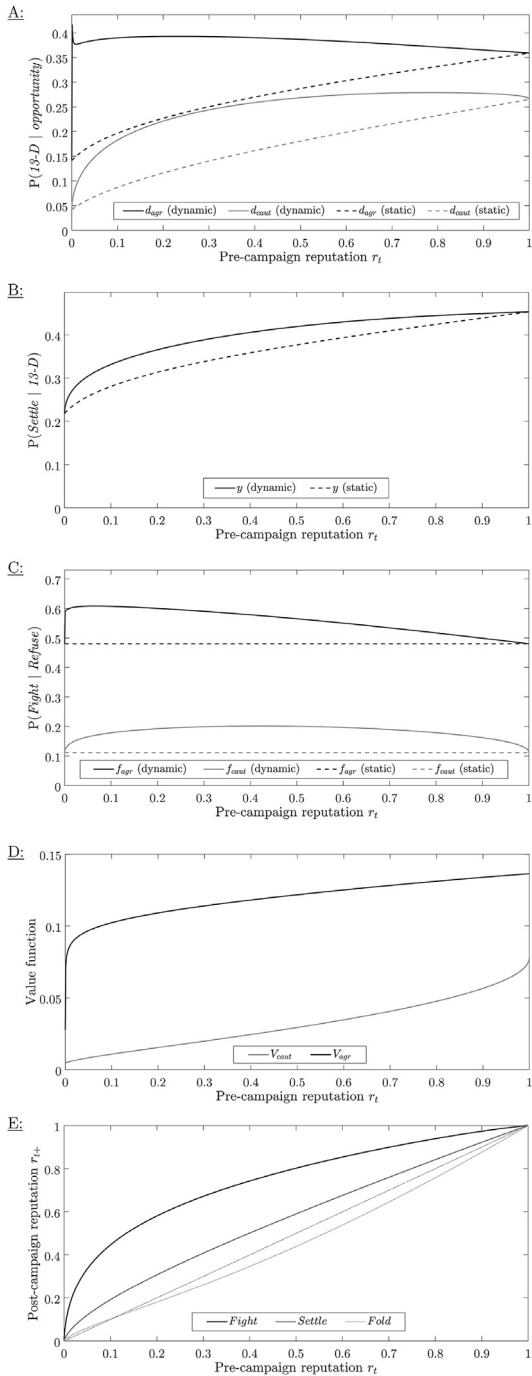
$$\text{and } \bar{F}_i^s \equiv \Delta. \quad (17)$$

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

### 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. Panel A of Fig. 1 shows both

<sup>9</sup> Events affecting activists in our sample consistent with type re-draws include Riley Investment Management's 2009 initial public offering (IPO) and Ramius Capital merging with the Cowen Group in 2009.



**Fig. 1. Estimated Equilibrium.** We plot equilibrium properties of our model using estimated parameters. Panel A shows the probability the activist chooses 13-D. Panel B shows the probability the target chooses *Settle*. Panel C shows the probability the activist chooses *Fight*. Panel D shows each type of activists' value function. Panel E 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.

types of A have higher likelihood of choosing 13-D ( $d_{caut}^s$  and  $d_{agr}^s$ ) when  $r_0$  is higher because they are more likely to receive profitable settlements (higher  $y^s$ ), as illustrated by Panel B. Panel C shows that  $r_0$  has no impact on either type of A's probability of fighting ( $f_{caut}^s$  or  $f_{agr}^s$ ) 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. First, both types of A initiate more proxy fights than they do in the static model ( $f_{caut} > f_{caut}^s$  and  $f_{agr} > f_{agr}^s$ ). These additional fights arise when a proxy fight's cost  $\tilde{F}_A$  is more than the direct payoff  $\Delta$  but is 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. Second, both types of A initiate more campaigns than they do in the static model ( $d_{caut} > d_{caut}^s$  and  $d_{agr} > d_{agr}^s$ ). 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 Panels D and E 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  $r_t$ .<sup>10</sup> Panel E shows the value function is much steeper for aggressive A when  $r_t$  is low because building and maintaining their reputation in the future is cheaper. As a result, an aggressive A increases 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 it reduces 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; and
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

In this section, 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

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

**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  $\mu$ , as specified in [Appendix D.2](#).

Random cost	Notation	Log distribution		Mapped parameter
		Mean	Precision	
A campaign cost	$\tilde{L}$	$\mu_L$	$\tau_L$	$d_{caut,0} = \mathbb{P}(13-D r_t = 0, \mu_L)$
M relative fight cost	$\frac{\tilde{F}_M}{B-\Delta}$	$\mu_M$	$\tau_M$	$y_0 = \mathbb{P}(\text{Settle} r_t = 0, \mu_M)$
Cautious A fight cost	$\tilde{F}_A$	$\mu_{caut}$	$\tau_A$	$f_{caut,0} = \mathbb{P}(\text{Fight} r_t = 0, \mu_{caut})$
Aggressive A fight cost	$\tilde{F}_A$	$\mu_{agr}$	$\tau_A$	$f_{agr,0} = \mathbb{P}(\text{Fight} r_t = 0, \mu_{agr})$

including the variables outlined in [Model Table 1](#) (*13-D*, *Proxy*, and *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 *A*'s track record. This dependence occurs due to reputation because *A*'s history determines their  $r_t$ , which in turn determines the observable 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 is that a unique parameterization maximizes the likelihood of observed data. In this section, we demonstrate 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 ([Fig. 2](#)). We then translate these comparative statics to empirical predictions for how each parameter affects the likelihoods of observable outcomes ([Fig. 3](#)).<sup>11</sup>

Instead of presenting estimates of the means of log costs ( $\mu_L$ ,  $\mu_M$ ,  $\mu_{caut}$ , and  $\mu_{agr}$ ), 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 a one-to-one mapping exists between these four probabilities and the corresponding  $\mu$  (see [D.2](#)). This mapping has no effect on the economics of

our model, and our results would be the same if we directly estimated the  $\mu$  instead.

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

We primarily identify  $d_{caut,0}$  and  $\tau_L$  using the observed campaign frequency (*13-D*/year) in the full sample and the difference in *13-D*/year when activists have strong and weak track records, making  $r_t$  unusually high or low. Increasing  $d_{caut,0}$  is equivalent to lowering average 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 Panel A in [Fig. 2](#). Increasing  $\tau_L$  decreases the noise in  $\tilde{L}$ , making *A* put relatively more weight on the expected payoff in the campaign. Panel B of [Fig. 2](#) shows this leads an aggressive *A*, who has higher expected payoffs, to initiate more campaigns across all  $r_t$ . It also makes a 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.

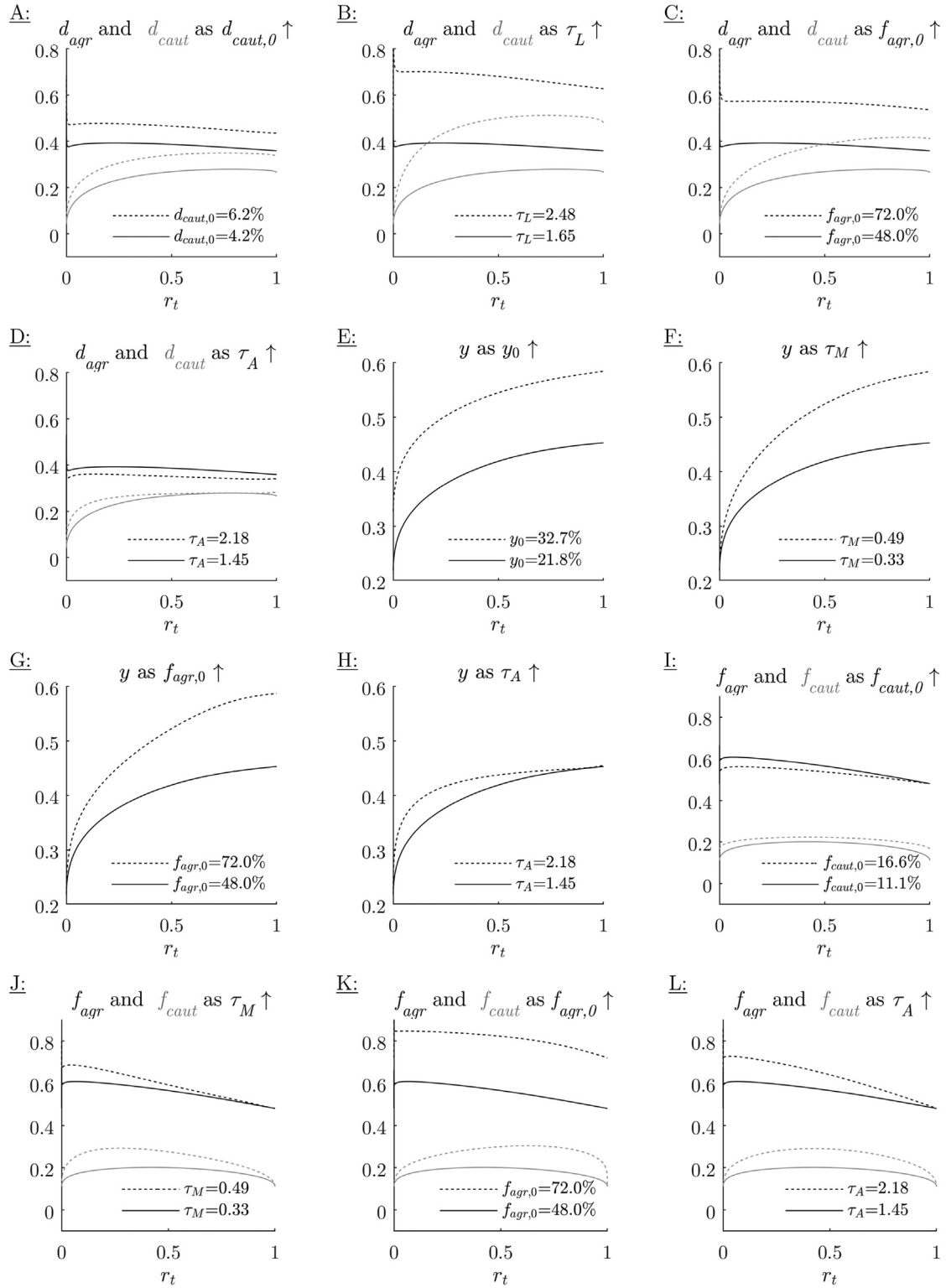
Panels A and B of [Fig. 3](#) show these comparative statics translate to the empirical prediction that  $d_{caut,0}$  and  $\tau_L$  determine the level and slope, respectively, of the relation between  $r_t$  and the model-implied *13-D*/year. All plots in [Fig. 3](#) show predictions for  $r_t$  between 0% and 10% to make level and slope effects easier to visually distinguish and because 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 $\tau_M$ )

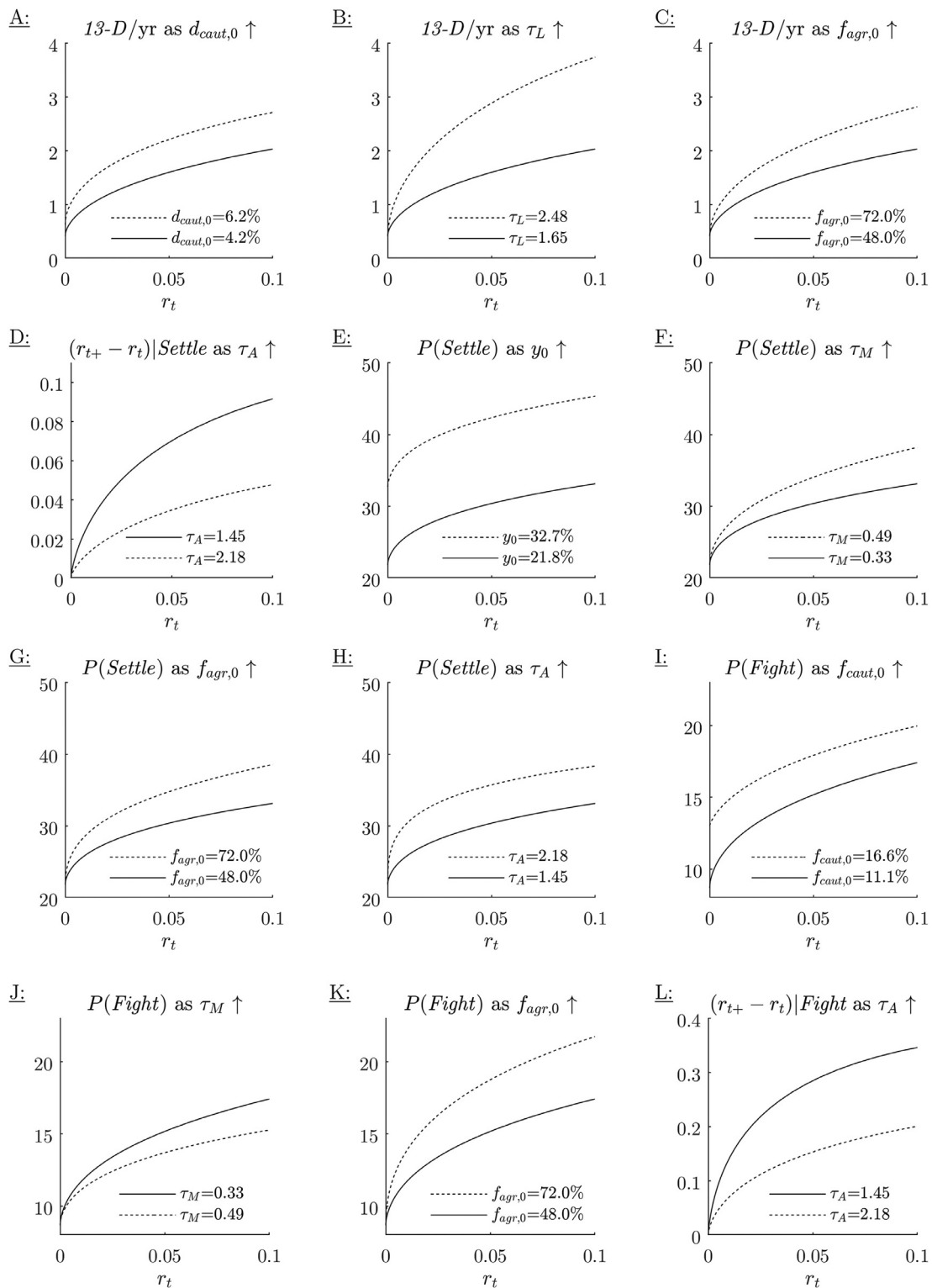
We primarily identify  $y_0$  and  $\tau_M$  using the average settlement frequency and the difference in settlement frequency when activists have strong versus weak track records, respectively. Increasing  $y_0$  is equivalent to increasing *M*'s average cost of a proxy fight, which increases the probability *M* settles across all  $r_t$ , as illustrated by Panel E of [Fig. 2](#). Increasing  $\tau_M$  reduces the noise in *M*'s settlement decision and therefore increases the sensitivity of  $y$  to  $r_t$ , as illustrated by Panel F of [Fig. 2](#). These comparative statics translate directly to predictions about the probability a campaign is settled [ $\mathbb{P}(\text{Settle})$ ], as illustrated by Panels E and F of [Fig. 3](#). We use observable target actions *a* to measure *Settle* empirically, as detailed in [Model Table 1](#).

<sup>11</sup> Changing any parameter affects equilibrium strategies at all three stages of the activism game and therefore all predicted likelihoods. For brevity, [Figs. 2](#) and [3](#) illustrate only the key distinct prediction(s) our model makes about each variable's impact that allow identification. The full set of plots are in Online Appendix Figs. OA1 and OA2.





**Fig. 2.** 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 A and aggressive A choose *13-D*, respectively;  $y$ , the probability M chooses *Settle*; and  $f_{caut}$  and  $f_{agr}$ , the probabilities cautious A and aggressive A choose *Fight*, respectively. The solid lines represent 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%. Gray lines represent cautious A's strategies.



**Fig. 3.** 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 campaign;  $P(Settle)$ , 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 and the dotted line presents the equilibrium functional form when a single parameter is increased by 50%.

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

We primarily identify  $f_{\text{caut},0}$  using the full-sample probability campaigns end in proxy fights. Increasing  $f_{\text{caut},0}$  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 Panel I of Fig. 2. The same plot illustrates that an aggressive A chooses *Fight* slightly less frequently with higher  $f_{\text{caut},0}$  because cautious A's added aggression decreases the reputation gained by choosing *Fight*. Panel I in Fig. 3 shows that these effects shift the probability of a proxy fight [ $\mathbb{P}(\text{Fight})$ ] upwards for A with low  $r_t$ , which drives up the predicted full-sample average because we estimate most activists have low  $r_t$ .

We primarily identify  $f_{\text{agr},0}$  using the differences in settlement and proxy fight frequencies between low and high  $r_t$  subsamples. Increasing  $f_{\text{agr},0}$  while holding fixed  $f_{\text{caut},0}$  widens the gap between cautious A and aggressive A in their frequency of proxy fighting (see Panel K of Fig. 2). This added difference also increases the slopes of the relations between  $r_t$  and both initiation and settlement decisions (see Panels C and G of Fig. 2). Combined, these comparative statics yield a distinct empirical prediction for  $f_{\text{agr},0}$ : It positively affects the slope of the relations between  $r_t$  and 13-D/year,  $\mathbb{P}(\text{Settle})$ , and  $\mathbb{P}(\text{Fight})$ , as illustrated by Fig. 3. Other variables increase one of these slopes but not the other slopes. For example, Fig. 3 shows that increasing  $\tau_M$  increases  $\mathbb{P}(\text{Settle})$  when  $r_t$  is high but decreases  $\mathbb{P}(\text{Fight})$  because fewer campaigns reach that stage. The unique prediction that allows us to identify  $\tau_M$  is therefore that it positively affects both the  $r_t$ - $\mathbb{P}(\text{Settle})$  relation and the  $r_t$ - $\mathbb{P}(\text{Fight})$  relation.

We primarily identify  $\tau_A$  using the frequency and success of campaigns after  $r_t$  has recently been updated. Increasing  $\tau_A$  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 Panels D, H, and L of Fig. 2. These effects combine to make increasing  $\tau_A$  result in a higher  $\mathbb{P}(\text{Settle})$  and  $\mathbb{P}(\text{Fight})$  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 ( $d_{\text{agr}}/d_{\text{caut}}$  and  $f_{\text{agr}}/f_{\text{agr}}$ ) is smaller. Panels D, H, and L of Fig. 3 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  $\tau_A$ .

### 3.6.4. Identifying remaining parameters ( $r_0$ , $\lambda_r$ , and $\Delta$ )

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.<sup>12</sup>

We identify  $\lambda_r$  using the apparent degree of persistence in the relation between past and future campaign outcomes. The arrival rate of type resets ( $\lambda_r$ ) 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. OA2. We therefore predict  $\lambda_r$  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 ( $\Delta$ ). For a given  $\Delta$ , our sample of campaign outcomes allows us to identify the distribution of costs and reputation as described above. Campaign outcome variables do not pin down the scale of successful projects. We thus identify  $\Delta$  using the model's prediction for the expected return to target shareholders at the start of a campaign:

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

We can therefore identify  $\Delta$  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:

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

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  $\theta$  using maximum likelihood and how we calibrate the remaining model parameters.

## 4. Data and estimation

In this section, we describe how we form our primary dataset and estimate our model.

### 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 SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database, and 5,910 campaigns using SharkWatch.<sup>13</sup> Of these, we keep 4,221 13-D filings and 3,874 campaigns from SharkWatch in which we successfully match target firms to the Compustat-CRSP Linked data and we identify

<sup>12</sup> For brevity and because they are straightforward to describe, we do not plot the effects of  $r_0$ ,  $\lambda_r$ , and  $\Delta$  in Figs. 2 and 3. We provide and discuss these plots in Online Appendix D.

<sup>13</sup> The SEC requires that investors file a beneficial ownership report on Form 13-D within ten days of initiating an activist campaign.

the activist is a financial institution.<sup>14</sup> We exclude campaigns for which the target security does not pertain to an operating corporation by requiring target CRSP share code be 10, 11, 18, 31, or 71 and dropping campaigns targeting firms with Standard Industry Classification (SIC) codes 6770 and 6726 (closed-end mutual funds and Special Purpose Acquisition 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 we attribute each campaign to the lead activist only. 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 nonoverlapping campaigns, 956 of which feature multiple activists. 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.<sup>15</sup> 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, which are the primary focus of empirical literature on activism (see Brav et al., 2008; 2010) and have the institutional structure most favorable to taking the costly actions required to build and maintain reputation (see Starks, 1987; Ackermann et al., 1999; 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 1801 campaigns by 603 unique non hedge fund activists targeting 1489 unique firms.

We face two data limitations that guide our sample construction and, because we assume future targets face the same limitations, the modeling choices discussed in Section 3.2. First, we cannot observe instances in which an activist identified a potential target but chose not to initiation a campaign. Second, no direct measure exists

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. (2020) 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 **a** of observable actions by the target to assess whether non-proxy campaigns are formally or informally settled.

The five variables in **a** are indicators for whether the target firm took each of five activist-friendly actions in the year following campaign initiation: *Reorg*, which indicates the target firm announces a reorganization, change in strategic direction, or discontinuation/downsizing of business; *Payout*, which indicates the target firm's quarterly payout (dividends plus stock repurchases) increases by more than 1% of assets; *CEO*, which indicates the CEO of the target firm departs; *Board*, which indicates a member of the target's board of directors departs or a new director is appointed due to activism; and *Acq*, which indicates the target firm announces a merger or acquisition, or announces that it seeks to sell or 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 varies 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 **a** even without activist intervention. Using  $\hat{\mathbf{a}}$  mitigates this possible explanation because it requires that 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

<sup>14</sup> To filter individual and nonfinancial corporation activists, we drop 13-D filings in which the activist Central Index Key (CIK) 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 nine-digit CUSIPs and quarterly filing dates for the SharkWatch campaigns.

<sup>15</sup> 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 DFAN14A, DEFR14A, DEFC14A, and DEFN14A) and apply the matching and filters outlined above with 13-D filings. For SharkWatch campaigns, we also use the provided “Proxy Fight” designation.



**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  $AbAction$  is  $Action - \widehat{Action}$ .  $Actions$  is the sum of these five indicators,  $\widehat{Actions}$  is the sum of the  $\widehat{Action}$ , and  $AbActions$  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.

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

contests, indicating that activists 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  $\hat{a}$  to initiate corporate restructurings, change CEOs, change board composition, and engage in M&A. 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 refers to activism-driven changes. These results validate that our sample captures most instances of activism and indicate that *Board* is an excellent measure of campaign success because it rarely occurs by chance. Perhaps surprisingly, activist targets are only marginally more likely to pay off activists by increasing payouts.

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

Even campaigns not featuring proxy fights are frequently successful, with targets taking each action more frequently than our predictive regressions would suggest. The average *Ab Actions* 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; 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:

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

$$\text{and } \Omega = [\delta, \sigma_{car}, \beta_{reorg}, \beta_{payout}, \beta_{ceo}, \beta_{board}, \beta_{acq}, \lambda_c], \quad (21)$$

where  $\sigma_{car}$  is the standard deviation of *CAR*. The first ten parameters ( $\theta$ ) 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 ( $\Omega$ ) either are impossible

to separately identify using available data or are estimable without the model. We therefore fix  $\Omega$  and estimate  $\theta$  using maximum likelihood.

We assign a value for  $\delta$  because we cannot distinguish empirically between a high value of  $\delta$ , which makes activists initiate more campaigns and proxy fights as investments in reputation, and higher values of campaign cost precision  $\tau_L$  and manager proxy cost precision  $\tau_A$ , which have the same two effects. We therefore base our estimation on the assumption that  $\delta = 0.9$ .<sup>16</sup> Similarly, we cannot distinguish empirically between a high arrival rate  $\lambda_c$ , 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  $\lambda_c$  is not unrealistically small.

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

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

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

$$L_c(\theta) = L_c^{gap}(\theta) \cdot L_c^{13-D}(\theta) \cdot L_c^{car}(\theta) \cdot L_c^{outcome}(\theta), \quad (22)$$

where  $L_c^{gap}(\theta)$  is the probability the activist initiates no campaigns until the date of their next 13-D,  $L_c^{13-D}(\theta)$  is the probability an opportunity arrives on the date of campaign  $c$  and the activist chooses 13-D,  $L_c^{car}(\theta)$  is likelihood of the target stock's reaction to the campaign initiation (CAR), and  $L_c^{outcome}(\theta)$  is the likelihood of the observed outcomes  $Proxy_c$  and  $a_c$  conditional on campaign initiation. Each of these likelihoods depends on  $r_t$ , as detailed in D.1. We assume CAR has distribution

$$CAR \sim N(\Delta \cdot \mathbb{P}(\text{project occurs} | r_t, 13-D), \sigma_{car}^2). \quad (23)$$

4. Compute overall likelihood  $l(\theta) = \sum_c \log(L_c(\theta))$ .

<sup>16</sup> 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).

## 5. Results and counterfactuals

In this section, we present and discuss our main 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  $\sigma_{car}$  and  $\beta_i$  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% level even when all other parameters are reestimated to maximize fit, as detailed in Online Appendix ??.

The projects that activists demand generate an estimated 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 with 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. Type resets do not necessarily imply type changes because we estimate that 98% of activists are cautious and therefore are likely to remain cautious after their type is redrawn.

Our estimated parameters imply the mean campaign cost ( $\bar{L}$ ) is 5.44% of the activist's position in the target and the mean proxy fight cost ( $\bar{F}_A$ ) is 8.68% for aggressive A and 19.44% for cautious A. These averages are substantial relative to the return from a successful campaign ( $\Delta = 6.62\%$ ), resulting in activists initiating campaigns and proxy fights only when cost realizations are unusually low. The relative size of average activist costs also illustrates 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. A potential economic reason the average costs in Gantchev (2013) are lower than our estimates, especially for cautious A, is that 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  $\tau_L$ ,  $\tau_M$ , and  $\tau_A$  determine how agents behave when  $r_t$  is strictly positive. Large values of  $\tau_L$  and  $\tau_M$  indicate stronger relations between  $r_t$  and campaign initiation and settlement decisions, respectively. Large values of  $\tau_A$  indicate more reputation-seeking fights. Small values of these precisions indicate agents follow mixed strategies independent of their  $r_t$ . We find that all three precisions are positive and statistically distinct from zero, indicating that constraining our model

**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 (SE) accounting for estimation error in  $\sigma_{car}$  and  $\beta$  and 95% confidence intervals (CI) 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 reestimated model parameters as well as the Wilks (1938) likelihood-ratio  $\chi^2$  statistic and its  $p$ -value. Our sample consists of 2,434 campaigns initiated by hedge funds during 1999–2016.

Panel A: Parameters estimated using maximum likelihood												
Parameter	Description	Estimate	SE	95% CI								
$\Delta$	Value of project A demands/market capitalization (percent)	6.62	(0.66)	[5.70, 7.35]								
$d_{caut,0}$	Probability cautious A chooses 13-D given $r_{t-} = 0$ (percent)	4.16	(0.63)	[2.78, 8.83]								
$\tau_L$	Precision log(Cost of campaign to A)	1.65	(0.19)	[0.48, 2.06]								
$y_0$	Probability M settles given $r_{t-} = 0$ (percent)	21.82	(2.43)	[12.87, 24.22]								
$\tau_M$	Precision log(M proxy fight cost/M project cost)	0.33	(0.15)	[0.11, 0.48]								
$f_{caut,0}$	Probability cautious A chooses Fight given $r_{t-} = 0$ (percent)	11.10	(2.81)	[2.44, 14.66]								
$f_{agr,0}$	Probability aggressive A chooses Fight given $r_{t-} = 0$ (percent)	48.03	(6.66)	[40.73, 60.38]								
$\tau_A$	Precision log(A proxy fight cost)	1.45	(0.64)	[0.72, 2.42]								
$r_0$	Unconditional probability A is aggressive (percent)	2.05	(1.94)	[1.00, 9.80]								
$\lambda_r$	Arrival rate of type resets (annualized)	0.19	(0.07)	[0.08, 0.36]								

Panel B: Parameters assumed or directly estimated												
Param.	Description	Value										
$\delta$	Activists' annual discount factor	0.90										
$\sigma_{car}$	Standard deviation of campaign announcement three-day CAR (percent)	8.99										
$\beta_{reorg}$	Added probability of reorganization in successful camp. (percent)	32.25										
$\beta_{payout}$	Added probability of payout increase in successful camp. (percent)	6.16										
$\beta_{ceo}$	Added probability of CEO change in successful camp. (percent)	17.53										
$\beta_{board}$	Added probability of board change in successful camp. (percent)	67.63										
$\beta_{acq}$	Added probability of M&A activity in successful camp. (percent)	30.76										
$\lambda_c$	Arrival rate of campaign opportunities (annualized)	10.00										

Panel C: Hypothesis tests												
Model	$\Delta$	$d_{caut,0}$	$\tau_L$	$y_0$	$\tau_M$	$f_{caut,0}$	$f_{agr,0}$	$\tau_A$	$r_0$	$\lambda_r$	$\chi^2$	$p$ -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%

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 reestimate 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  $\theta$  in a no-reputation world because many parameters  $\theta$  generate the same static game equilibrium. One of many equivalent formulations for any no-reputation equilibrium features  $r_0 = 0$ , meaning we can estimate the no-reputation model with only four parameters:  $\Delta$ ,  $d_{caut,0}$ ,  $y_0$ , and  $f_{caut,0}$ .

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  $r_t$  strongly predicts campaign frequency and outcomes. We therefore find a high likelihood ratio  $\chi^2$  statistic and strongly reject the no-reputation hypothesis.

Another 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. Unlike the no-reputation hypothesis, each stage game does not feature the same equilibrium strategy. Instead, each game is played according to the  $r_0 = 0$  static equilibrium for cautious A and the  $r_0 = 1$  static equilibrium for aggressive A. To make the full-information model estimable by econometricians

who do not directly observe activist type, we assume activist types do not change and assign each activist the type that maximizes the likelihood of their full-sample set of campaign outcomes. We therefore identify the full set of parameters  $\theta$  except for  $\tau_A$  (because  $r_t$  is never between zero and one) and  $\lambda_r$  (because activist types do not change).

We find that the full-information model fits the data best when a cautious  $A$  chooses  $13-D$  9.12% of the time and  $Fight$  12.36% of the time, while an aggressive  $A$  chooses  $13-D$  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.<sup>17</sup> Aggressive  $A$ s are less common ( $r_0 = 0.85\%$  versus  $2.05\%$ ) 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 full 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 ( $13-D$ ,  $Ab\ Actions|Proxy = 0$ ,  $CAR$ , 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.

### 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.<sup>18</sup> 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 it 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.

No significant differences exist 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 allows only across-activist variations, whereas our model also allows within-activist variation depending on  $r_t$ . This shortcoming, together with the additional within-activist evidence we discuss in Section 5.4, leads 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 (wrt) each parameter ( $\theta_j$ ), defined as:

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

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  $\Delta$ , which as we describe in Section 3.6 directly affects average  $CAR$ . We show that this is the case, with average model-predicted  $CAR$  having an elasticity with respect to changes in  $\Delta$  equal to one, which is higher than any other parameter. Furthermore, changing  $\Delta$  only

<sup>17</sup> Aggressive  $A$ 's probability of choosing  $13-D$  and  $M$ 's probability of settling with aggressive  $A$  are computed from full-information  $d_{\text{caut},0}$ ,  $\tau_L$ ,  $y_0$ , and  $\tau_M$ .

<sup>18</sup> See Appendix D.1 for details on how we handle activists only present in part of our sample.



**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 in which 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 which 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 (SE) 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 parameter. We only tabulate elasticities larger than 0.25 in absolute value. Elasticities highlighted in Bold 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.

Moment:	Data		Model-estimated value			Elasticity with respect to									
	Value	(SE)	Baseline	No reputation	Full information	$\Delta$	$d_{caut,0}$	$\tau_L$	$y_0$	$\tau_M$	$f_{caut,0}$	$f_{agr,0}$	$\tau_A$	$r_0$	$\lambda_r$
Full sample															
Mean CAR	2.82	(0.25)	2.80	2.82	2.90	<b>1.00</b>			0.54						
Mean 13-D	1.00	(0.08)	0.93	1.06	1.08		<b>0.45</b>	0.44			-0.25				
Mean <i>Ab Actions</i>   <i>Proxy</i> = 0	0.65	(0.04)	0.52	0.51	0.55				<b>0.86</b>						
Mean Proxy	14.30	(1.67)	13.74	14.30	11.87				-0.28	-0.27	<b>0.66</b>				
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	<b>1.60</b>	-0.86	0.66	-0.62	1.15			
Mean <i>Ab Actions</i>   <i>Proxy</i> = 0	0.37	(0.17)	0.50	0.00	0.36					<b>0.60</b>	-0.42	<b>1.16</b>			
Mean Proxy	25.25	(3.63)	15.43	0.00 $\downarrow\downarrow$	20.43				-0.66	<b>-0.78</b>	<b>0.79</b>				
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	<b>-0.36</b>		
Mean <i>Ab Actions</i>   <i>Proxy</i> = 0	-0.02	(0.11)	0.21	0.00 $\uparrow$	0.08					0.32		0.58	<b>-0.26</b>		
Mean Proxy	1.74	(3.63)	6.70	0.00	4.40				-0.76	-0.99		0.31	<b>-0.28</b>		
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 <i>Ab Actions</i>   <i>Proxy</i> = 0	0.06	(0.08)	-0.07	0.00	-0.03		0.64	1.03	-0.78	-0.25			0.27	<b>0.42</b>	
Mean Proxy	-1.43	(2.20)	-2.11	0.00	-1.94		0.66	1.05		1.11	-0.35	0.46	0.31	<b>0.35</b>	
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			<b>-0.56</b>
Mean <i>Ab Actions</i>   <i>Proxy</i> = 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		<b>-0.54</b>
Mean Proxy	23.80	(9.56)	5.14	0.00	2.88		-0.69	-2.69	1.23	-0.67		-0.64	0.38		<b>-0.49</b>

significantly affects mean CAR, meaning  $\Delta$  is primarily identified by the sample average CAR.

Consistent with Fig. 3, Table 3 shows  $d_{caut,0}$  and  $\tau_L$  both directly affect mean predicted 13-D, but  $\tau_L$  has a larger impact on the predicted difference in mean 13-D between high and low  $r_t$  observations.  $d_{caut,0}$  and  $\tau_L$  are unique in the sense that other parameters either do not affect both these moments (e.g.,  $y_0$ ) or have large effects on moments unrelated to  $d_{caut,0}$  and  $\tau_L$  (e.g.,  $f_{caut,0}$ ). We therefore conclude  $d_{caut,0}$  and  $\tau_L$  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. 3,  $y_0$  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  $\tau_M$  and  $f_{agr,0}$  on the likelihoods of both settlements and proxy fights. Consistent with these predictions, Table 3 shows that increasing  $\tau_M$  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* rela-

tion, which strengthens as aggressive As are more likely to choose *Fight*, but has the same positive effect on the  $r_t$ -*Ab Actions*|*Proxy* = 0 relation. Our estimates of  $\tau_M$  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. 3, 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.

Figs. 2 and 3 show that increasing  $\tau_A$  narrows the gap in campaign and proxy fight frequency between cautious A 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  $\tau_A$  increases in cases for which A's reputation has recently updated upward. We therefore focus on the subsample in which 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  $\tau_A$ . The  $\tau_A$  column illustrates this pattern, with all three relative moments for the recently updated subsample decreasing in  $\tau_A$ . Table 3 also shows that increasing  $\tau_A$  affects other moments. 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.,  $\tau_L$ ) or have large effects on moments unrelated to  $\tau_A$  (e.g.,  $f_{agr,0}$ ).

As discussed in Section 3.6, we predict that  $r_0$  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 activists' careers relative to the overall sample.

Finally, increasing  $\lambda_r$  primarily affects the rate at which  $r_t$  reverts toward  $r_0$  between campaigns. As a result, Table 3 shows that increasing  $\lambda_r$  only substantially affects moments in situations where a long gap exists since the prior campaign (more than a year) and  $r_t$  is still above  $r_0$ , meaning  $r_t$  is reverting downward and will be further lowered by increasing  $\lambda_r$ . We therefore primarily identify  $\lambda_r$  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 (**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%.

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 are Starboard Value and Icahn Enterprises. Both have 77 campaigns in our sample have around 30 proxy fights, generate unusually many target actions, and have average  $r_t$  above the 90th percentile of the overall distribution. Fig. 4 shows the evolution of these activists'  $r_t$ , both of which are above 75% for the past decade and peak above 99%. Panel C of Fig. 4 also shows the evolution of  $r_t$  for Loeb Partners, which initiated only 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. 4,  $r_t$  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. 4 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, which Fig. 4 illustrates built a strong  $r_t$  from 2005 to 2009 and then suddenly became inactive, possibly due to its parent company's 2009 IPO, initiating only one additional campaign in 2013.

### 5.4. Effects of reputation and model fit

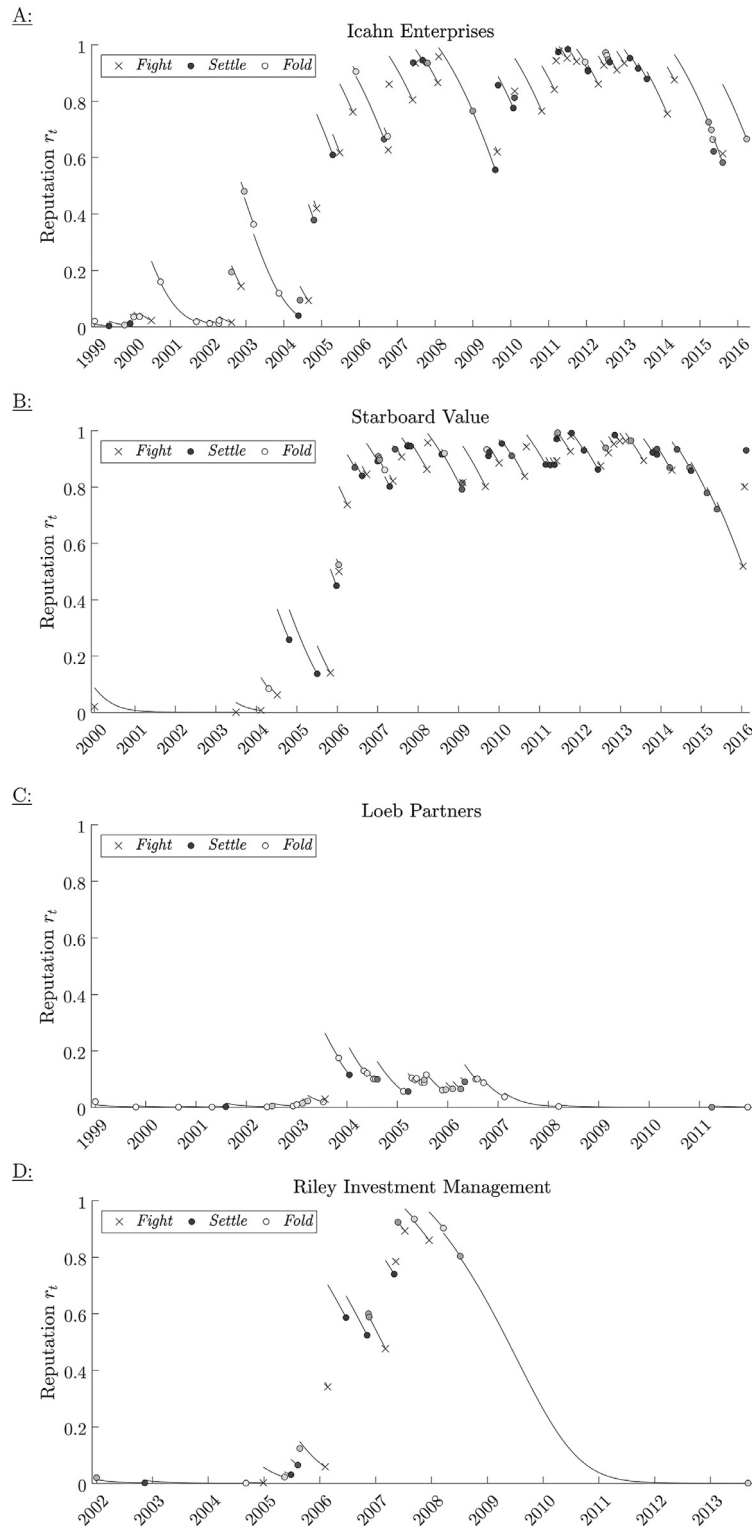
We assess our model's fit and measure the effects of reputation by estimating model-implied equilibrium strategies for each campaign in our sample, computing what these strategies imply for the distributions of outcomes, and comparing these predictions with observed outcomes. We do so using the same process as for Table 3, described in Section 5.2. Instead of local elasticities of moments to parameters, we present levels of model-implied and data moments for gradations of  $r_t$  and, more important, estimates of unobservable equilibrium strategies and motivations gleaned from our estimated model.

Panel A of Table 5 shows that our model predicts that 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  $r_t$ .

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 with the likelihood of drawing  $\tilde{L}$  low enough that the expected profit from the individual campaign is positive. From this comparison, we estimate that 80.08% of 13-D decisions in our sample had positive expected single-campaign profits, and 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 with only 23.86% of the time for low  $r_t$  activists, as depicted in Panel B of Fig. 1. This translates into a strong relation between  $r_t$  and the average  $AbActions$  in campaigns without a proxy fight, which our model predicts varies from 0.41 for low  $r_t$  campaigns to 0.91 for high  $r_t$  campaigns. Our model fits the data well for medium and high  $r_t$  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  $AbActions$  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  $AbActions$  than predicted by



**Fig. 4.** 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.

**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  $r_t$ . *AbActions* 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											
	Mean	Variance	Percentile								
			1st	5th	10th	25th	50th	75th	90th	95th	99th
$r_{t+}$	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 <i>AbActions</i>	Mean <i>CAR</i>
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 Management	47.36	16	8	0.88	4.27%
4. Clinton Group	44.07	29	12	1.62	5.13%
5. Riley Investment Management	42.79	24	7	1.75	3.02%
6. Vertex Capital Adv	28.26	11	3	1.55	1.50%
7. Steel Partners	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 Partners	24.51	16	9	1.56	8.92%
11. Bulldog Investment	24.15	24	12	1.13	0.41%
12. Voce Capital Management	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 Partners	16.64	16	4	2.25	0.25%
17. PL Capital	16.37	39	10	0.79	3.27%
18. Shamrock Partners	15.53	19	3	1.63	0.22%
19. Millennium Management	14.69	44	0	0.82	-0.30%
20. Sandell Asset Management	14.38	15	8	2.20	2.19%
21. ValueAct Capital Management	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 Associates	8.79	60	0	0.57	2.76%

our model, with only medium  $r_t$  campaigns matching the model closely. The model fits average *CAR* well (2.80% versus 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 and 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 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 with those predicted by the model. These regressions abandon the structure of our model, which predicts nonlinear relations, and so should be viewed as providing additional descriptive moments. They also offer several advantages over

the summary statistics in Table 5, allowing us to assess which dimensions of the data the model fits well, compare our results with other empirical work on activism, and control for other potentially relevant activist characteristics.<sup>19</sup>

Table 6 present linear regression coefficients for predicting *13-D*, *AbActions*, *CAR*, and *Proxy* using  $r_t$ , without activist fixed effects in Panel A and with them in Panel B. In both panels, 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 thousand 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.

With the exception of *Proxy* in Panel A and *CAR* in Panel B, the magnitude of the estimated coefficients are close

<sup>19</sup> 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).



**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 that have positive expected profits in the current campaign, with the remainder listed as "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.

$r_t$ (percent) range:	All	[0, 0.5]	[0.5, 5]	[5, 50]	[50, 100]
<b>Panel A: Activist-days sorted by <math>r_t</math></b>					
Percent of activist-days	100.00	65.85	23.11	7.96	3.07
Strategies					
$d_{caut}$ (percent of opportunities)	8.74	6.10	9.88	20.04	27.60
$d_{agr}$ (percent of opportunities)	39.57	40.35	37.84	38.97	37.36
Outcomes					
13-D (model) ( $\times$ 365)	1.00	0.58	1.17	2.99	3.50
13-D (data) ( $\times$ 365)	0.93	0.62	1.03	2.29	3.48
Motivations					
Short-term profitable (percent of 13-D)	80.08	84.75	73.20	71.77	91.82
Reputation building (percent of 13-D)	19.92	15.25	26.80	28.23	8.18
<b>Panel B: Campaigns sorted by <math>r_t</math></b>					
Percent of campaigns	100.00	48.81	22.51	19.76	8.92
Strategies					
$y$ (percent of 13-D)	28.55	23.86	26.97	34.89	44.11
$f_{caut}$ (percent of Refuse)	14.62	12.61	14.54	18.41	17.45
$f_{agr}$ (percent of Refuse)	58.98	59.26	60.19	60.07	51.96
Outcomes					
<i>Ab Actions</i> (model)	0.65	0.52	0.61	0.83	1.08
<i>Ab Actions</i> (data)	0.78	0.73	0.69	0.77	1.24
<i>Ab Actions</i>   <i>Proxy</i> = 0 (model)	0.51	0.41	0.48	0.66	0.91
<i>Ab Actions</i>   <i>Proxy</i> = 0 (data)	0.65	0.63	0.58	0.66	1.00
CAR (model) (percent)	2.80	2.25	2.61	3.55	4.61
CAR (data) (percent)	2.82	2.78	2.53	2.45	4.59
<i>Proxy</i> (model) (percent)	13.74	10.12	12.46	18.79	25.55
<i>Proxy</i> (data) (percent)	14.30	11.62	10.22	15.38	36.87
Motivations					
Short-term profitable (percent of <i>Fight</i> )	81.17	87.95	76.62	68.77	90.16
Reputation building (percent of <i>Fight</i> )	18.83	12.05	23.38	31.23	9.84

enough to the model-predicted magnitudes that we fail to reject the model null, suggesting that 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 changing a parameter such as  $\tau_A$  to make the model-implied relation between  $r_t$  and *Proxy* stronger would simultaneously strengthen the relations between  $r_t$  and CAR and between  $r_t$  and *Ab Actions*, 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 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 downward in finite samples.<sup>20</sup> 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

<sup>20</sup> The technical reason for this bias is that these regressions fail the strict exogeneity condition discussed in Wooldridge (2010) and Grieser and Hadlock (2019).

**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 and *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 parentheses. For each null, \*\*\* indicates we reject at the 1% level; \*\*, 5%; and \*, 10%.

	<i>13-D</i> (1)	<i>Ab Actions</i> (2)	<i>Ab Actions</i>   <i>Proxy</i> = 0 (3)	<i>CAR</i> (4)	<i>Proxy</i> (5)
<i>Panel A: Main regressions</i>					
Data coefficient	4.43	0.71	0.55	2.60	34.26
Standard error	(0.53)	(0.18)	(0.18)	(0.70)	(4.32)
Simulated coefficient (model null)	4.19	0.77	0.72	3.53	19.88**
Simulated coefficient (no reputation null)	-0.02***	-0.07***	-0.03***	0.04***	-4.10***
Simulated coefficient (full information null)	3.39**	0.72	0.59	3.25	33.08
<i>Panel B: Activist fixed effects</i>					
Data Coefficient	1.59	-0.06	-0.06	0.88	7.86
Standard error	(0.38)	(0.17)	(0.20)	(1.19)	(6.62)
Simulated coefficient (model null)	2.13	-0.08	0.26	3.20*	-0.33
Simulated coefficient (no reputation null)	-3.05***	-1.52**	-0.58***	0.03	-1.03
Simulated coefficient (full information null)	-2.64***	-0.45**	-0.27	0.02	-0.31
<i>Panel C: Robustness</i>					
$r_t$	2.82*** (0.73)	0.93*** (0.23)	0.74*** (0.25)	2.91** (1.22)	40.04*** (8.42)
<i>Past CAR</i> <sub>250</sub>   <i>Proxy</i>	0.06 (0.14)	-0.16 (0.18)	-0.09 (0.19)	-0.41 (0.80)	0.06 (5.56)
<i>Past CAR</i> <sub>250</sub>   <i>Hi Act</i>	0.14 (0.16)	0.03 (0.17)	0.00 (0.16)	0.73 (1.13)	4.71 (4.58)
<i>Past CAR</i> <sub>250</sub>	-0.01 (0.12)	-0.24 (0.17)	-0.24 (0.17)	-0.05 (1.25)	0.83 (3.77)
<i>Log Portfolio Size</i>	0.01 (0.02)	-0.00 (0.03)	0.00 (0.03)	0.04 (0.16)	-2.85*** (0.77)
<i>Portfolio Turnover</i>	-0.20** (0.08)	-0.12 (0.07)	-0.08 (0.08)	-0.02 (0.51)	-1.54 (2.35)
<i>Number of Prior Campaigns</i>	0.06*** (0.01)	-0.00 (0.00)	0.00 (0.00)	-0.01 (0.02)	-0.08 (0.08)
<i>Stake Size</i>		-0.69 (0.54)	-0.08 (0.54)	0.43 (3.94)	-49.70*** (18.49)
<i>Top Investor Hedge Fund</i>	0.02 (0.13)	0.10 (0.09)	0.14 (0.10)	-0.13 (0.64)	3.80 (2.34)

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 of Panel B, which are significantly larger than the negative coefficients we find in full-information simulations. The combined evidence in Panels A and B of Table 6 illustrate why the likelihood ratio test presented in Table 2 rejects 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. The full-information null is rejected at the 5% level in three of the specifications in Table 6 and 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*, mimic the experience and reputation measures used in Boyson et al. (2016) and

Krishnan et al. (2016), respectively. Three other variables, *Past CAR*<sub>250</sub>|*Proxy*, *Past CAR*<sub>250</sub>|*Hi Act*, and *Past CAR*<sub>250</sub>, 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

**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 choose *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 thousand 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, in basis points (bp).

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

change in a world without reputation.<sup>21</sup> 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 that the activist is aggressive. In this no-reputation counterfactual, activists and targets play the same strategy in every campaign opportunity; that is, the static equilibrium strategy when  $r_0 = 2.05\%$ . The second counterfactual we consider sets  $r_0 = 0$ , removing the possibility of aggressive *A* from the model. In this no aggressive *A* counterfactual, cautious *A* and *M* play their zero-reputation strategies  $d_{caut,0}$ ,  $y_0$ , and  $f_{caut,0}$ . In the third counterfactual, *M* observes *A*'s type directly, removing the role for reputation and learning. In this full information counterfactual, the  $r_t = 0$  equilibrium prevails for all of cautious *A*'s opportunities, and 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 thousand 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.<sup>22</sup> We find that cautious and aggressive *As* 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. Even when cautious *A*'s type remains unknown in the no-reputation counterfactual, they still initiate fewer campaigns than in our baseline model due to the absence of reputation-building incentives.

Conditional on campaign initiation, we also find that targets would be less likely to settle without reputation. In our baseline model, managers settle in 27.44% of campaigns, compared with 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* chooses *Fight*  $f_{agr,0} = 48.03\%$  of the time, both less than their likelihood of fighting in the dynamic equilibrium.

Combining these effects, Table 7 shows that average payoffs for target shareholders per campaign opportunity

<sup>21</sup> 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.

<sup>22</sup> Because we only estimate the distribution of target managers' cost of proxy fights ( $\bar{F}_M$ ) relative to their net private costs of the project ( $B - \Delta$ ), we cannot quantify managers' payoffs in absolute terms.

would decline by at least 48% in all three counterfactuals. Target shareholders receive nothing if the project does not occur and a return of  $\Delta$  if it does. Target 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  $A$ s 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  $A$ s, 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 reestimating our model under a variety of alternative parameterizations, empirical implementations, and modeling assumptions. As detailed in Online Appendix E, we consider different values for activists' discount factor ( $\delta$ ) and the arrival rate of campaign opportunities ( $\lambda_c$ ), 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 ( $\hat{a}$ ), random variations across campaigns in the expected return for target shareholders after a successful campaign ( $\Delta$ ), and proxy fights succeeding only a fraction  $\phi$  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  $\lambda_c$  results in proportionally smaller estimates of the baseline frequency with which activists choose *13-D* ( $d_{caut,0}$ ). Similarly, random variations in  $\Delta$  serve as substitutes for random variation in campaign costs ( $\tilde{L}$ ), resulting in higher estimates of their precision ( $\tau_L$ ).

More important, we find that our main economic results are consistent across alternative assumptions. Reputation-building incentives explain between 15% and 30% of observed aggressive behavior, and without reputation activists would create between 35%–60% less value for target shareholders.<sup>23</sup> The reason these effects are more consistent is they are identified from the changes in av-

erage campaign frequency and outcomes as a function of reputation observed in the data. While the specific parameters generating this increase can 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 with 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 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 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 research could examine these possibilities using a similar approach to this paper. More broadly, our methodology could 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

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

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

$$\begin{aligned} & \mathbb{P}(agr|r_t, \text{no camp.}) - r_t \\ &= \frac{\mathbb{P}(\text{no camp.}|r_t, agr)r_t}{\mathbb{P}(\text{no camp.}|r_t, agr)r_t + \mathbb{P}(\text{no camp.}|r_t, caut)(1 - r_t)} \end{aligned} \quad (A.2)$$

$$= \frac{[(1 - d_{agr}(r_t))\lambda_c + (1 - \lambda_c)]r_t}{[(1 - d_{agr}(r_t))\lambda_c + (1 - \lambda_c)]r_t + [(1 - d_{caut}(r_t))\lambda_c + (1 - \lambda_c)](1 - r_t)} - r_t, \quad (A.3)$$

which simplifies to the value given in Eq. (A.1).

<sup>23</sup> The only exception is if we decrease  $\lambda_c$  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.



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

$$\mathbb{P}(\mu_A = \mu_{agr} | r_0, 13-D) = r_0. \quad (\text{A.4})$$

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  $106 \times 1$  grid of  $r_t$ :

$$\mathbf{r} \equiv [0, \Phi([-6, -5, -4, -3.5, -3.43, -3.36, \dots, 3.36, 3.43, 3.5, 4]), 1], \quad (\text{A.5})$$

where  $\Phi$  is the standard normal cumulative distribution function. 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 omit 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

$$p_f(r_t) = \frac{r_t d_{agr}(r_t) f_{agr}(r_t) + (1 - r_t) d_{caut}(r_t) f_{caut}(r_t)}{r_t d_{agr}(r_t) + (1 - r_t) d_{caut}(r_t)} \quad (\text{A.6})$$

We use value function iteration to find equilibrium strategies  $d_i$ ,  $y$ , and  $f_i$  along with value functions  $V_i$  in four steps.

1. Find  $d_i$ ,  $y$ , and  $f_i$  assuming a flat value function  $V_i(r) = 0$  by numerically searching for values that satisfy Eqs. (11), (13), and (15).
2. Find the reputation updating function both between campaigns and after campaigns. Eq. (A.1) 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 Eqs. (7) and (8) combined with Bayes' rule as follows:

$$\begin{aligned} r_{t+} | (\text{Proxy} = 1, r_t = r) \\ = \frac{rd_{agr}(r) f_{agr}(r)}{rd_{agr}(r) f_{agr}(r) + (1 - r) d_{caut}(r) f_{caut}(r)} \end{aligned} \quad (\text{A.7})$$

$$\begin{aligned} \text{and } r_{t+} | (\text{Proxy} = 0, r_t = r) \\ = \frac{rd_{agr}(r) \mathbb{P}(\text{Settle} | \mathbf{a}, r)}{rd_{agr}(r) + (1 - r) d_{caut}(r)} \\ + \frac{rd_{agr}(r) (1 - f_{agr}(r)) \mathbb{P}(\text{Fold} | \mathbf{a}, r_t)}{rd_{agr}(r) (1 - f_{agr}(r)) + (1 - r) d_{caut}(r) (1 - f_{caut}(r))}. \end{aligned} \quad (\text{A.8})$$

The posterior probabilities a campaign was settled given  $\text{Proxy} = 0$  are

$$\begin{aligned} \mathbb{P}(\text{Settle} | \mathbf{a}, r_t = r) \\ = \frac{\mathbb{P}(\mathbf{a} | \text{Settle}, r) \mathbb{P}(\text{Settle} | r)}{\mathbb{P}(\mathbf{a} | \text{Settle}, r) \mathbb{P}(\text{Settle} | r) + \mathbb{P}(\mathbf{a} | \text{Fold}, r) \mathbb{P}(\text{Fold} | r)} \end{aligned} \quad (\text{A.9})$$

$$\text{and } \mathbb{P}(\text{Fold} | \mathbf{a}, r, r_t = r) = 1 - \mathbb{P}(\text{Settle} | \mathbf{a}, r), \quad (\text{A.10})$$

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

3. Find  $V_i$  using

$$\mathbf{V}_i = \mathbb{E}(\mathbf{\Pi}_i) + \delta^{1/365} \mathbf{\Sigma}_i \mathbf{V}_i \quad (\text{A.11})$$

$$\Rightarrow \mathbf{V}_i = (\mathbf{I}_{106} - \delta^{1/365} \mathbf{\Sigma}_i)^{-1} \mathbb{E}(\mathbf{\Pi}_i), \quad (\text{A.12})$$

where  $\mathbf{V}_i$  is a  $106 \times 1$  vector of  $V_i(r_t)$  values for  $r_t \in \mathbf{r}$ ,  $\mathbb{E}(\mathbf{\Pi}_i)$  is a  $106 \times 1$  vector expected per day profits for  $A$  with type  $i$ ,  $\delta$  is the annualized discount factor,  $\mathbf{\Sigma}_i$  is a  $106 \times 106$  transition probability matrix describing the likelihood of reputation transitions in a single day, and  $\mathbf{I}_{106}$  is the identity matrix. We compute this transition probability matrix using Eq. (A.1) discretized daily, the distribution of possible observed outcomes Proxy and  $\mathbf{a}$  conditional on a campaign occurring [from Eq. (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 with 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 Wharton Research Data Services (WRDS) SEC Analytics tool, SharkWatch, and our estimation, which we describe in Section 4.3.

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

$\text{Past CAR}_{250} | \text{HiAct}$  is the average  $\text{CAR}_{250}$  in all the activist's prior campaigns with  $\text{AbActions}$  above the full-sample median and zero if the activist has no such campaigns.

$\text{Past CAR}_{250}$  is the average  $\text{CAR}_{250}$  in all the activist's prior campaigns and zero if the activist has no prior campaigns.

$\text{Prior Campaigns}$  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, described in Section 4.3.

$r_{t+}$  is our estimate of the activist's post-campaign reputation, described 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, and cash flow and balance sheet data from Compustat, CRSP, and SharkWatch.

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

$\widehat{Ab\ Actions}$  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 it seeks to sell or 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<sub>250</sub>* 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 (versus 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 or 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.

*One-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. Eq. (C.1) outlines each regression:

$$a_{j,i,t+4} = \alpha_{i,t} + \gamma_{i,t} \cdot X_{j,t} + \epsilon_{j,i,t+4}, \quad (C.1)$$

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<sub>j,t</sub>*, *EBIT/Assets<sub>j,t</sub>*, *Net Leverage<sub>j,t</sub>*, *Payout/Assets<sub>j,t</sub>*, *Capex/Assets<sub>j,t</sub>*, *Book-to-Market<sub>j,t</sub>*, *Inst Ownership<sub>j,t</sub>*, and *One-Year Return<sub>j,t</sub>*.<sup>24</sup>

Online Appendix Table OA1 shows the average coefficients across each of our 56 quarterly cross-sectional predictive regressions, with  $t$ -statistics calculated using the

<sup>24</sup> We define in detail how we calculate each of the actions and characteristics in Appendix B.

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

$$L_c(\theta) = L_c^{gap}(\theta) \cdot L_c^{13-D}(\theta) \cdot L_c^{car}(\theta) \cdot L_c^{outcome}(\theta). \quad (D.1)$$

$L_c^{gap}(\theta)$  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

$$L_c^{gap}(\theta) = \sum_{s=t+1}^{t+d-1} \left[ \left( 1 - \frac{\lambda_c}{365} \right) + \frac{\lambda_c}{365} (r_s(1 - d_{agr}(r_s)) + (1 - r_s)(1 - d_{caut}(r_s))) \right], \quad (D.2)$$

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 December 31st, 2016.<sup>25</sup>

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

$$L_c^{13-D}(\theta) = \frac{\lambda_c}{365} (r_t d_{agr}(r_t) + (1 - r_t) d_{caut}(r_t)). \quad (D.3)$$

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

$$L_c^{car}(\theta) = \phi \left( \frac{CAR - \mathbb{P}(\text{Settle or Fight} | r_t, 13-D)}{\sigma_{car}} \right) \quad (D.4)$$

$$\text{and } \mathbb{P}(\text{Settle or Fight} | r_t, 13-D) = y(r_t) + (1 - y(r_t)) p_f(r_t), \quad (D.5)$$

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

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

$$L_c^{outcome}(\theta) = \begin{cases} (1 - y(r_t)) p_f(r_t) & \text{if Proxy} = 1 \\ y(r_t) \mathbb{P}(\mathbf{a} | \text{Settle}) + (1 - y(r_t)) \times (1 - p_f(r_t)) \mathbb{P}(\mathbf{a} | \text{Fold}) & \text{if Proxy} = 0 \end{cases} \quad (D.6)$$

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

To ease the interpretation of our model's parameters, we map means of log costs  $\mu_L$ ,  $\mu_M$ ,  $\mu_{agr}$ , and  $\mu_{caut}$  to what

they imply for strategies when reputation equals zero. This mapping is:

$$f_{caut,0} = \Phi(\tau_A(\log(\Delta) - \mu_{caut})), \quad (D.7)$$

$$f_{agr,0} = \Phi(\tau_A(\log(\Delta) - \mu_{agr})), \quad (D.8)$$

$$y_0 = 1 - \Phi \left( \tau_M \left( \log \left( \frac{1 - f_{caut,0}}{f_{caut,0}} \right) - \mu_M \right) \right), \quad (D.9)$$

$$d_{caut,0} = \Phi(\tau_L(\log(\bar{L}_{caut,0}) - \mu_L)), \quad (D.10)$$

$$\text{and } \bar{L}_{caut,0} = y_0 \Delta + (1 - y_0) f_{caut,0} \\ (\Delta - \mathbb{E}[\tilde{F}_A | \tilde{F}_A < \Delta, \mu_A = \mu_{caut}]). \quad (D.11)$$

### D.3. Simulating samples

Our analyses in [Tables 6 and 7](#) use samples simulated from the model. For a given parameterization of the model  $\theta$ , and given restrictions on the information set, we compute equilibrium strategies and reputation dynamics as described in [Section 3.3](#) and [Appendix A](#). With these in hand, we simulate samples using the following six-step 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  $t_0$ , 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  $\lambda_r$ , and at each date re-assign a new randomly drawn type, forming a complete path for the  $A^{(i)}$ 's true type.
3. Draw random campaign opportunity dates according to rate  $\lambda_c$ .
4. Starting with the first campaign at  $t_0$ , randomly draw costs  $\bar{L}$ ,  $\bar{F}_M$ , and  $\bar{F}_A$  and compute the resulting campaign outcome. From this outcome, draw random  $\mathbf{a}$  using [Eq. \(7\)](#). Then compute post-campaign reputation  $r_{t+}$  and, based on [Eq. \(A.1\)](#), 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 a sample is generated matching the size of our empirical sample.

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<sup>25</sup> 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.

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