Reputation and Investor Activism:
A Structural Approach

Online Appendix

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Abstract

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

Appendix A. Variation in idea quality across activists

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

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

First, we estimate the ability of measures for past aggressiveness and idea quality to predict how target firms and the stock market respond to future campaigns. We measure aggressiveness using $PastProxy$, the fraction of prior campaigns by the activist with a proxy fight. Online Appendix Table 1 shows that $Past\ Proxy$ strongly predicts market reactions to future campaigns (CAR) and the number of abnormal activist-friendly actions taken by targets ($Ab\ Actions$) in non-proxy campaigns.[1]

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

1. $PastCAR_{250}|Proxy$, average CAR_{250} in the activist's past campaigns with $Proxy = 1$, where CAR_{250} is the target's cumulative abnormal return from 10 trading days prior to the campaign announcement to 250 trading days after.

2. $PastCAR_{250}|Hi\,Act$, average CAR_{250} in the activist's past campaigns with $Ab\,Actions$

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[1]We also find mixed evidence past *Ab Actions* and past campaign frequency, the two other variables affecting r_t in our model, predict responses to future campaigns.

above the full-sample median.

3. *Past CAR_{250}*, average CAR_{250} in all the activist's past campaigns.

Online Appendix Table 1 shows that none of these measures for activist-specific idea quality predict future abnormal target actions or campaign announcement returns.

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

$$x_c = a + \rho \cdot Past\, \overline{x}_{c-} + \epsilon_c, \tag{1}$$

where x_c is a measurable outcome of campaign c and $Past\, \overline{x}_{c-}$ is the average value of x_c in prior campaigns by the activist initiating campaign c. The outcome variables we use are *Proxy*, *AbActions*, *13-D*, *CAR_3*, *$CAR_{250}|Proxy$*, *$CAR_{250}|HiAct$*, and *CAR_{250}*, each defined above. The results, in Panel C of Online Appendix Table 1, show that proxy fighting, target actions, campaign frequency, and campaign announcement returns are all persistent within-activist, suggesting that activist types vary across these dimensions. By contrast, we find that none of the measures of idea quality are persistent within activist.

Given the noise in year-long abnormal returns, the evidence in Online Appendix Table 1 that return-based measures of idea quality are not predictive or persistent does not conclusively rule out the possibility of differences in idea quality across activists. However, we argue this noise is precisely what makes it difficult for targets to learn about activists' average idea quality. Learning about aggressiveness, by contrast, is much more direct and therefore much more amenable to reputation effects in practice, as illustrated by the results in Online Appendix Table 1. For these reasons, our model focuses on activist types differing by aggressiveness rather than idea quality.

Appendix B. Standard errors

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

$$\boldsymbol{\Theta} \equiv \begin{bmatrix} \sigma_{car} & \beta & \theta \end{bmatrix}', \tag{2}$$

we can therefore combine our estimations of σ_{car} and β_i with our maximum-likelihood estimation of θ into a unified method of moments estimator solving:

$$\frac{1}{N} \sum_{c=1}^{N} m_c(\boldsymbol{\Theta}) = 0, \tag{3}$$

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

$$m_c(\boldsymbol{\Theta}) = \begin{bmatrix} (CAR_c - \overline{CAR})^2 - \sigma_{car}^2 \\ (a_{1,c} - \hat{a}_{1,c} - \beta_1)(Proxy = 1) \\ \vdots \\ (a_{5,c} - \hat{a}_{5,c} - \beta_5)(Proxy = 1) \\ \frac{\partial \mathsf{L}_c(\theta)}{\partial \theta_1} \\ \vdots \\ \frac{\partial \mathsf{L}_c(\theta)}{\partial \theta_{10}} \end{bmatrix}, \tag{4}$$

with $\mathsf{L}_c(\theta)$ defined as the conditional likelihood function for campaign c given in Equation (22).[2] This moment-based approach produces the same estimates of Θ we get from separately estimating σ^2_{car}, β, and θ but allows us to compute standard errors for Θ which account for estimation error in $\hat{\sigma}^2_{car}$ and $\hat{\beta}$ using the standard method of moments asymptotic results:[3]

$$\sqrt{N}\left(\hat{\Theta} - \Theta_0\right) \sim N\left[\mathbf{0}, \mathbf{A}^{-1}\mathbf{B}\mathbf{A}'^{-1}\right].$$ (5)

where the matrices A and B using:

$$\hat{\mathbf{A}} = \frac{1}{N}\sum_{c=1}^{N}\frac{\partial m_c(\Theta)}{\partial \Theta'},$$ (6)

$$\hat{\mathbf{B}} = \frac{1}{N}\sum_{c=1}^{N}\sum_{d=1}^{N}m_c(\Theta)m_d(\Theta)' \cdot \mathbf{1}\,(c \text{ and } d \text{ initiated by same activist})\,.$$ (7)

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

Appendix C. Robustness

C.1. Exogenous parameter choices

As described in Section 4.3, we fix exogenous values for two parameters we have no hope of identifying in the data: activist's discount factor δ and the arrival rate of campaign opportunities λ_c. For our main results, we fix $\delta = 0.9$ and $\lambda_c = 10$. We now examine how changing these values affects our main results. For each alternative parameter value, we re-estimate the main parameters θ using maximum likelihood and summarize our main results. Specifically, we estimate the fraction of *13-D* and *Fight* choices by activists that are taken

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[2]In principle, we have enough independent variation across different outcome variables to estimate the full parameter vector Θ using maximum likelihood. We choose not to because finding a global maximum with 16 independent variables (σ^2_{car}, five β_i, and ten θ_i) is computationally challenging, and because we have relatively direct and low-noise estimates of β and σ_{car}.

[3]Note that this estimator is just-identified because there are 16 total parameters and 16 moments, so we do not have to use a GMM weighting matrix.

at a short-term loss to build reputation, as described in Section 5.4, and the decreases in campaign success in a no-reputation counterfactual, as described in Section 5.5.

We begin with two alternative values for δ, 0.85 and 0.95. Panel A of Online Appendix Table 2 shows that changing δ has only a small impact on parameter estimates. Panel B shows that our main results only vary slightly with changes in δ. Increasing δ to 0.95 makes activist more patient, resulting in a greater willingness to take costly actions as investments in reputation, which translates into larger estimates for the counterfactual drop is aggressiveness without reputation. Decreasing δ has the opposite effect. However, Panel B shows these effects are small; across all three values of δ, we estimate around 20% of observed campaign initiations and proxy fights are driven by reputation-building incentives, and between 46% and 57% of the value added for target shareholders would disappear without reputation.

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

The only alternative parameterization with substantially weaker results is if we set the arrival rate of campaign opportunities, λ_c, to 5 per year or lower. Without frequent enough campaign opportunities, the value of building a strong reputation is diminished, which in turn diminishes reputation-seeking behavior and the overall economic importance of reputation. Such infrequent arrivals of campaign opportunities is also inconsistent with the behavior of high reputation activists in the data. For example, high reputation activists[4] initiate more than 5 campaigns in 35% of years, which would be very unlikely with $\lambda_c = 5$ even if high reputation activists always chose *13-D*. As long as λ_c is large enough to avoid this constraint, increases in λ_c are observationally equivalent to decreases in the probability of choosing *13-D*,

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[4]Defined as having average reputation over 50%, the cutoff used in Table 4).

and therefore have only minimal effects on our main results.

C.2. Empirical implementation

We next show our results are robust to two alternative empirical implementations. The first is using longer-term target stock returns around campaign initiation dates. Our baseline results use 3-day CARs from the [-1,1] window around the 13-D announcement date. As an alternative specification, we consider 20-day CARs from the [-10,10] window. The longer return window has the advantage of including any increase in prices before or after the 13-D filing attributable to price pressure by activists. However, it has the disadvantage of including much more noise from other events affecting the firm in the two month window, which increases the standard deviation of CAR from 9% to 18%. Column (8) of Online Appendix Table 2 shows that this change has a negligible impact on our parameter estimates and main results.

The second alternative implementation we consider uses fixed values for $\hat{a}_i$, the probability the target takes action i in the absence of activism, across all campaigns rather than campaign-specific fitted values from the cross-sectional regression described in Appendix C. While campaign-specific $\hat{a}_i$ allows us to address the possibility high reputation activists systematically select different targets, it introduces the concern that our results are driven by choices we made it modelling $\hat{a}_i$. To mitigate these concerns, we re-estimate the model with $\hat{a}_i$ fixed for all campaigns to equal its mean value from our main specification. Column (9) of Online Appendix Table 2 shows this change also has almost no impact on our main results.

C.3. Modelling assumptions

Finally, estimate two variations of our model under alternative assumptions. First, we consider the possibility that the average return for target shareholders when the campaign is successful, Δ, varies randomly across campaigns instead of being fixed.[5] We do so by adding

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[5]Online Appendix A discusses the possibility that different different activists have different Δ.

random variation across campaigns in $\tilde{\Delta}$, assuming that the realization of $\tilde{\Delta}$ is common knowledge for both the activist and target prior to the campaign, and is independent of the other random cost realizations (e.g. $\tilde{L}$). Because this possibility necessitates solving the model independently for each possible realization of $\tilde{\Delta}$, we limit the distribution to three discrete possibilities:

$$\tilde{\Delta} = \overline{\Delta} \times \begin{cases} 0.5 & \text{w.p. } \frac{1}{3}, \\ 1.0 & \text{w.p. } \frac{1}{3}, \\ 1.5 & \text{w.p. } \frac{1}{3}, \end{cases} \tag{8}$$

This approach results in the same set of exogenous parameters to estimate as in our baseline model but with $\overline{\Delta}$ replacing the fixed Δ.

We plot the equilibrium strategies in this alternative model in Online Appendix Figure 2. As illustrated by these plots, the main effect of random variation in $\tilde{\Delta}$ is added 'noise' in the relations between r_t and observed decisions. Even high r_t activists are unlikely to file a 13-D, receive a settlement, or initiate a proxy fight when $\tilde{\Delta}$ is low, while low r_t activists are quite aggressive and successful when $\tilde{\Delta}$ is high. However, average behavior across realizations of Δ is quite similar to what we find in the baseline model, which may not be surprising given that shape offers the best fit to observed data.

Column (10) of Online Appendix Table 2 presents the parameter estimates and main results for this alternative model with variations in Δ. We estimate a larger precision (smaller standard deviation) for the cost of initiating campaign (τ_L), indicating variations in $\tilde{\Delta}$ serve as a substitute for variations in ($\tilde{L}$). We also find substantially-less aggressive behavior for activists with $r_t = 0$ and $\tilde{\Delta} = \overline{\Delta}$. The reason for that the baseline rates of campaign initiation, settlements, and proxy fights are all quite low, meaning we estimate that most of them occur in the third of campaigns with $\tilde{\Delta} = 1.5\overline{\Delta}$.

Despite changes to parameter estimates when $\tilde{\Delta}$ is random, the main economic results

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

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

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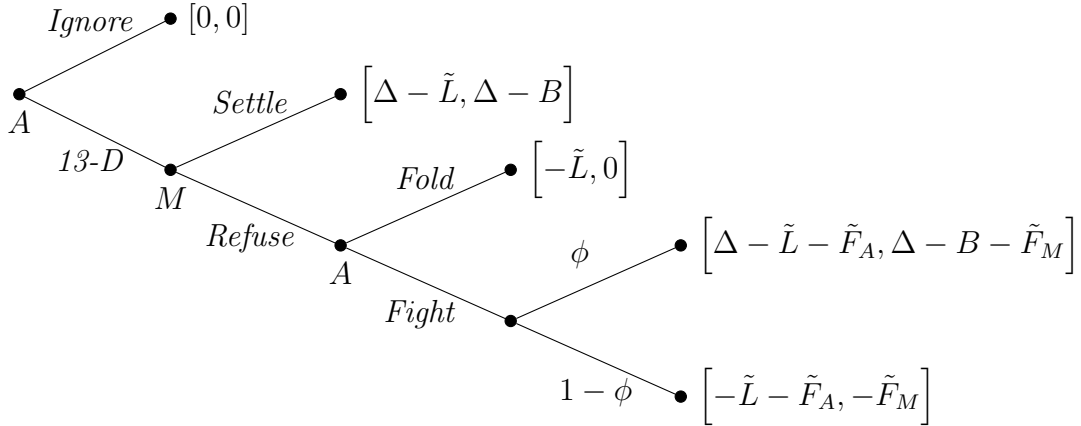
The main effect of this change is in our estimates of β_i, the added likelihood target takes observable action i given a successful campaign. We identify these parameters using the additional likelihood of the action (average $a_i - \hat{a}_i$) in campaigns featuring a proxy fight. In our baseline model,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

$$\beta_i = \frac{1}{N_{proxy}} \sum_{c=1}^{N_{proxy}} (a_{i,c} - \hat{a}_{i,c}),\tag{9}$$

where N_{proxy} is the number of campaigns with $Proxy = 1$. In the alternative model where

only a fraction ϕ of proxy fights are successful, we define β_i^ϕ as the additional likelihood of each action when the project occurs, meaning that conditional on an observed proxy fight (but not conditioning on its outcome), the added probability of action i is $\phi\beta_i^\phi$, and we have:

$$\beta_i^\phi = \frac{1}{N_{proxy}} \frac{1}{\phi} \sum_{c=1}^{N_{proxy}} (a_{i,c} - \hat{a}_{i,c}) = \frac{\beta_i}{\phi} \tag{10}$$

Numerically, this results in the following changes in our estimates of β_i:

Parameter	Description	Baseline	$\phi = 0.57$
β_{reorg}	Added prob. of reorganization in successful camp. (%)	32.3	56.6
β_{payout}	Added prob. of payout increase in successful camp. (%)	6.2	10.8
β_{ceo}	Added prob. of CEO change in successful camp. (%)	17.5	30.7
β_{board}	Added prob. of board change in successful camp. (%)	67.6	100.0
β_{acq}	Added prob. of M&A activity in successful camp. (%)	30.8	54.0

Note that we truncate β_{board} above at 100%, meaning that in this alternative model successful campaigns always result in a change in board composition.

Holding cost parameters fixed, allowing some proxy fights to fail makes activists less likely to initiate proxy fights and managers less likely to settle. However, to fit the properties of the data, our estimation adjusts the cost distribution parameters so that proxy fights and settlements are once again as likely in the model as they are empirically. The resulting estimates, presented in Column (11) of Online Appendix Table 2, indicate only small differences in the main implications of our model: reputation-building incentives explain 12% of observed proxy fights and 19% of campaign initiations, and without reputation activists would create 39% less value for target shareholders.

Appendix D. Reputation and cumulative target returns

Tables 5 and 6 show that the empirical relation between r_t and CAR is weaker than the model-implied relation. One potential reason is that market prices do not react to the

information contained in campaign initiations entirely during the $[-1,+1]$ announcement window we focus on. Instead, targets of high reputation activists could outperform targets of low reputation activists prior to the announcement window due to information leakage, or after the announcement window due to a delayed reaction.

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

Appendix E. Non hedge fund activists

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

Panel A of Online Appendix Table 3 compares summary statistics for the hedge fund and non hedge fund samples. We find that non hedge fund activists initiate fewer campaigns and have lower average *Ab Actions*, CAR, and *Proxy*. We further decompose non hedge fund activists into six categories: the first is Gamco, a mutual fund manager that has by far the most campaigns in our sample of any activist (345), hedge fund or otherwise. We summarize them in a separate category because they behave differently than other activists, rapidly filing 13-Ds despite almost never initiating proxy fights and generating low average

Ab Actions. Other mutual funds only lead 38 total campaigns, but these campaigns appear to be as successful as those by hedge funds. Private equity funds, broker dealers, pension funds, and other activists categories all have lower average CAR and $Proxy$, and all but pension funds extract fewer *Ab Actions* in non-proxy campaigns than hedge funds.

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

Given the apparent differences in equilibrium behavior for non hedge fund activists illustrated in Panel A of Online Appendix Table 3, it is possible a different set of model parameters explains the non hedge fund sample better than applying our baseline reputation measure. We evaluate this possibility by re-estimating our model in the non hedge fund sample, and find the substantially different set of parameters presented in Panel B of Online Appendix Table 3. Non hedge fund activists propose less-valueable projects (lower Δ) and fight less frequently (lower $f_{caut,0}$ and $f_{agr,0}$). On the other hand, they initiate more campaigns (higher $d_{caut,0}$), and are more sensitive to changes in settle probability when making campaign initiation decisions (higher τ_L).

The biggest difference between hedge fund activists and other activists and is in the behavior of aggressive types. Aggressive type hedge funds choose *Fight* with much higher probability than cautious hedge funds, resulting in a strong relation between reputation and campaign success in addition to campaign frequency. Aggressive type non hedge funds choose *Fight* only slightly more often than their cautious counterparts, weakening the relation between reputation and campaign success. At the same time, due the higher τ_L, aggressive

non hedge funds initiate campaigns much more frequently. In short, high reputation hedge fund activists fight more, which translates to future success, while high reputation non hedge fund activists merely campaign more, which does not.

Appendix F. Computing our reputation measure

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

Computing our reputation measure r_t entails the following steps:

1. Assemble a panel dataset of activist campaigns with the following variables (as defined in Appendix B of the paper): the date of the 13-D filing, an activist identifier, CAR, $Proxy$, Acq, $\widehat{Acq}$, $Board$, $\widehat{Board}$, CEO, $\widehat{CEO}$, $Payout$, $\widehat{Payout}$, $Reorg$, and $\widehat{Reorg}$.

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

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

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

5. Iterate through each activists' campaigns computing pre- and post-campaign reputations. Prior to the first campaign for each activist r_t equals $\underline{r}_0$, which is defined so that the activist's reputation conditional on initiated a campaign equals the unconditional reputation r_0:

$$\mathbb{P}(\mu_A = \mu_{agr}|\underline{r}_0, \textit{13-D}) = r_0. \qquad (11)$$

Using equilibrium strategies when $r_t = \underline{r}_0$ and observed $Proxy$ and $\mathbf{a}$ for the first

campaign, compute the post-campaign reputation, then compute the pre-campaign reputation for the second campaign based on the number of days using Equation (24), and continue iterating until the activists' last campaign.

References

Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The performance of hedge funds: Risk, return, and incentives, *The Journal of Finance* 54, 833–874.

Gantchev, Nickolay, 2013, The costs of shareholder activism: Evidence from a sequential decision model, *Journal of Financial Economics* 107, 610–631.

Starks, Laura T, 1987, Performance incentive fees: An agency theoretic approach, *Journal of Financial and Quantitative Analysis* 22, 17–32.

Stulz, René M, 2007, Hedge funds: Past, present, and future, *Journal of Economic Perspectives* 21, 175–194.

Online Appendix Figure 1: Reputation and Cumulative Target Returns

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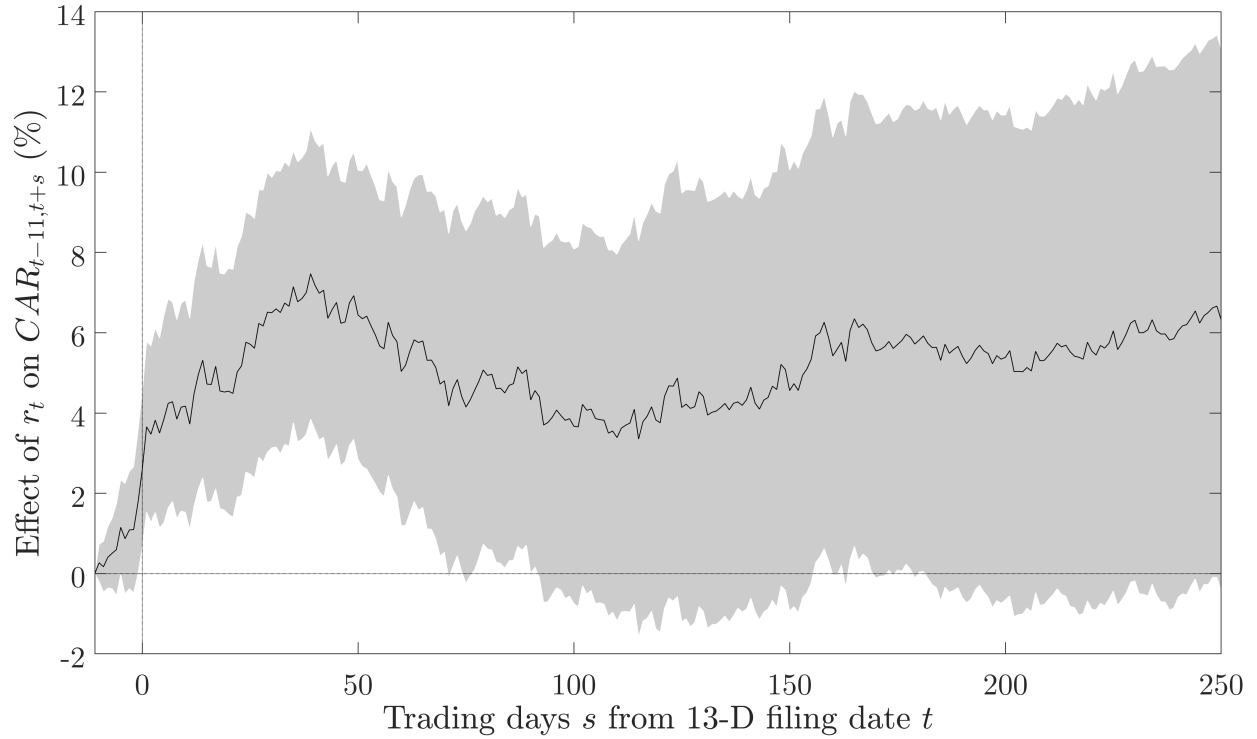
Online Appendix Figure 2: Estimated Equilibrium with Random Δ

We plot equilibrium properties of our alternative model wherein the value of the project Δ randomly takes one of three values, using the estimated parameters presented in Online Appendix Table 2. The first plot shows the probability each type of activist chooses *13-D*. The second shows the probability the target chooses *Settle*. The third shows the probability each type of activist chooses *Fight*. All three plots are a function of pre-campaign reputation r_t. The subscript *agr* represents the aggressive type activist, while *caut* represents the cautious type activist. Hi Δ, Med Δ, and Lo Δ represent the three possible values of Δ, 6.9%, 4.6%, and 2.3%, respectively.
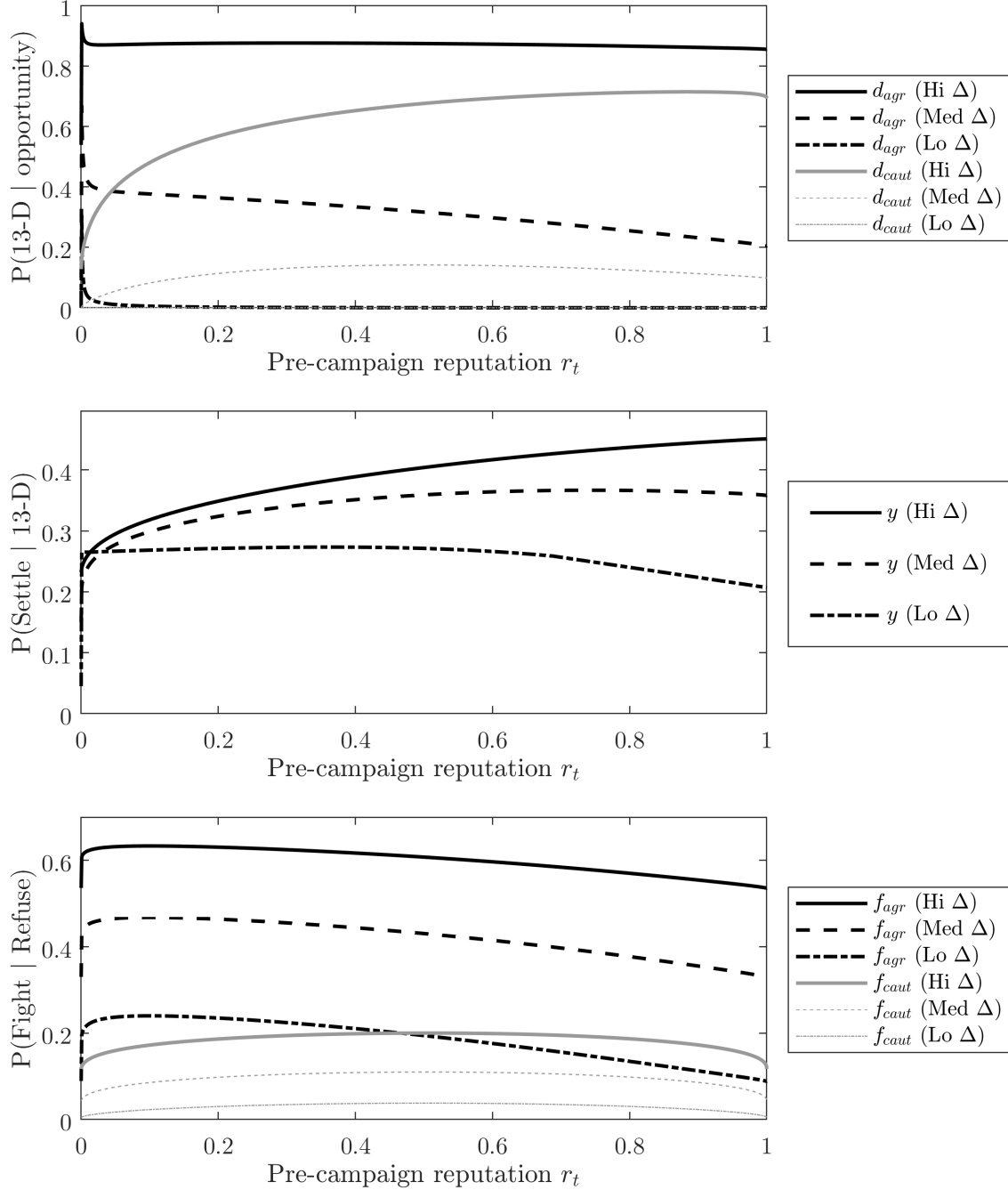
Online Appendix Table 1: Aggressiveness and Idea Quality

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past Proxy	11.06***						8.94**
	(4.07)						(4.05)
Past Ab Actions		10.57***					7.64*
		(3.98)					(4.01)
Past 13-D			12.16***				11.08***
			(3.86)				(3.84)
Past CAR$_{250}$|Proxy				−6.30*			−5.91*
				(3.29)			(3.49)
Past CAR$_{250}$|Hi Act					−2.23		−4.99
					(3.35)		(5.22)
Past CAR$_{250}$						0.14	3.27
						(3.21)	(4.93)

Panel B: Predicting Campaign Announcement Returns (CAR × 100)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past Proxy	0.59***						0.61***
	(0.22)						(0.22)
Past Ab Actions		0.22					0.08
		(0.24)					(0.22)
Past 13-D			0.41*				0.33
			(0.23)				(0.24)
Past CAR$_{250}$|Proxy				−0.10			−0.07
				(0.21)			(0.22)
Past CAR$_{250}$|Hi Act					−0.20		−0.68
					(0.32)		(0.50)
Past CAR$_{250}$						0.10	0.56
						(0.29)	(0.44)

Panel C: Campaign Outcome Persistences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Proxy	*Ab Actions*	*13-D*	*CAR$_3$*	*CAR$_{250}$| Proxy*	*CAR$_{250}$| Hi Act*	*CAR$_{250}$*
$\hat{\rho}$	0.58***	0.39**	0.41***	0.28***	0.02	−0.01	−0.02
	(0.08)	(0.16)	(0.05)	(0.10)	(0.15)	(0.09)	(0.10)

Online Appendix Table 2: Robustness

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

Panel A: Parameter Estimates

	Baseline	$\delta = 0.85$	$\delta = 0.95$	$\lambda_c = 5$	$\lambda_c = 7.5$	$\lambda_c = 15$	$\lambda_c = 20$	CAR_{20}	Const. $\hat{a}_i$	Rand. Δ	$\phi = 0.57$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Δ (%)	6.62	6.63	6.68	6.75	6.66	6.10	6.62	6.33	6.70	4.59	6.48
$d_{caut,0}$ (%)	4.16	4.12	3.94	8.36	5.58	2.86	1.55	4.36	4.20	0.02	4.74
τ_L	1.65	1.72	1.87	6.49	2.10	1.51	1.37	1.64	1.69	2.74	1.63
y_0 (%)	21.82	21.92	22.05	25.46	22.64	21.26	20.70	21.87	21.65	14.96	22.73
τ_M	0.33	0.33	0.34	0.21	0.34	0.33	0.32	0.33	0.34	0.28	0.37
$f_{caut,0}$ (%)	11.10	11.20	11.54	13.78	12.10	10.84	10.68	11.35	11.40	4.26	11.51
$f_{agr,0}$ (%)	48.03	47.51	46.10	48.91	46.01	46.47	44.94	46.94	46.66	33.02	51.23
τ_A	1.45	1.55	1.61	1.00	1.36	1.73	2.01	1.25	1.44	1.31	0.54
r_0 (%)	2.05	2.03	2.25	1.69	1.71	11.55	2.61	2.20	1.90	2.58	2.61
λ_r	0.19	0.19	0.19	0.19	0.19	0.18	0.17	0.15	0.19	0.17	0.17

Panel B: Main Results

Rep. building (% of *13-D*)	19.92	19.44	23.97	20.50	20.77	26.55	21.79	19.75	20.24	18.01	19.30
Rep. building (% of *Fight*)	18.83	18.52	22.03	7.47	16.19	27.98	23.41	16.31	18.21	28.77	12.04
Ch. in Pr(*13-D*) w/out rep. (%)	−39.56	−38.30	−47.77	−14.24	−39.70	−43.76	−50.72	−36.68	−40.23	−30.67	−32.14
Ch. in Pr(*Settle*) w/out rep. (%)	−13.22	−13.36	−15.52	−2.94	−11.19	−15.09	−14.84	−12.20	−13.12	−36.13	−10.39
Ch. in Pr(*Fight*) w/out rep. (%)	−29.65	−28.65	−32.92	−18.48	−25.11	−40.37	−33.50	−27.73	−28.45	−64.17	−24.64
Ch. in $\mathbb{E}$ tgt. payoff w/out rep. (%)	−48.37	−46.90	−56.75	−16.59	−47.10	−53.37	−59.26	−45.06	−48.88	−34.84	−39.27

Online Appendix Table 3: Non Hedge Fund Activists

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

Panel A: Moments using hedge fund parameter estimates

	Hedge Funds	All Non-HF	Gamco	Other MFs	PE Funds	Broker Dealers	Pension Funds	Other
Campaigns	2434	1801	345	38	122	111	105	1069
Activists	420	603	1	10	11	19	15	547
Mean(*13-D*) ($\times 365$)	1.00	0.73	19.31	0.48	1.03	0.83	1.37	0.41
Mean(*Ab Actions*)	0.78	0.54	0.32	0.89	0.28	0.21	0.68	0.64
Mean(*CAR*) (%)	2.82	1.66	1.56	2.96	2.03	1.23	0.58	1.77
Mean(*Proxy*) (%)	14.30	6.39	2.32	5.26	0.82	0.90	5.71	9.07
corr(r_t, *13-D*) (%)	3.28	8.92	−0.28	3.31	2.07	1.79	4.71	1.55
corr(r_t, *Ab Actions*) (%)	13.62	−5.84	−0.10	11.16	2.24	−11.59	7.74	0.73
corr(r_t, *CAR*) (%)	6.65	−0.10	5.86	1.04	2.55	5.40	−2.56	−3.33
corr(r_t, *Proxy*) (%)	22.52	−5.66	9.16	−8.82	−1.32	−5.56	−5.51	−5.76
Mean r_t (%)	10.81	6.60	28.26	1.41	0.84	0.54	8.81	0.92
Median r_t (%)	0.55	0.40	21.46	0.39	0.40	0.34	1.39	0.40
90th perc r_t (%)	41.87	22.32	63.01	3.83	1.84	1.33	27.86	1.36

Panel B: Non hedge fund parameter estimates

	Δ	$d_{h,0}$	τ_L	y_0	τ_M	$f_{caut,0}$	$f_{agr,0}$	τ_A	r_0	λ_r
Hedge Funds	6.62	4.16	1.65	21.82	0.33	11.10	48.03	1.45	2.05	0.19
All Non HF	5.73	3.61	5.22	22.86	1.26	9.13	19.81	0.24	0.18	0.25

Panel C. Comparing moments and equilibrium properties

	Hedge Funds	All Non HF
corr(r_t, *13-D*) (%)	3.28	9.55
corr(r_t, *Ab Actions*) (%)	13.62	−8.74
corr(r_t, *CAR*) (%)	6.65	0.07
corr(r_t, *Proxy*) (%)	22.52	−8.04
13-D (% of opp.)	9.34	4.44
Settle (% of camp.)	27.44	23.38
Fight (% of refusals)	16.85	9.15
Shareholder payoff/opp (bp)	24.53	7.75