Hedge Fund Activism Skill

March 17, 2023

Abstract

Not all hedge fund activists are equally successful. We use a Markov Chain Monte Carlo Bayesian estimation algorithm to isolate a time-invariant hedge fund activist-specific skill component from campaign announcement returns. Considerable differences in this skill component emerge: Measuring performance with CARs, top-skill activists outperform bottom-skill activists by up to 20 percentage points. Out-of-sample tests confirm that our skill estimates are informative about future performance. Differences in skills are also evident in hedge fund activists' campaign characteristics. Highly skilled activists are associated with higher target firm takeover premiums, improved long-term target performance, and a more versatile use of campaign tactics.

Keywords: Hedge fund activism, performance persistence, Bayesian estimation, skill

JEL Classifications: G13, G23, G34, C11

Don't confuse luck with skill when judging others and especially when judging yourself! – Carl Icahn

1 Introduction

Hedge funds have developed considerable interest in engaging with target firms over the past two decades, fueling much of the prevalence of shareholder activism in the United States. Between 2001 and 2018, activist campaigns initiated by hedge funds against U.S. targets account for 49% of all events of activism in Corporate America.[1] Undoubtedly, their involvement in shareholder activism has been a profitable endeavor, and announcements of hedge fund activism campaigns have resulted in average abnormal returns of about 5% for target firm shareholders over the years (Brav, Jiang and Kim, 2015). Despite their growing prominence and success as shareholder activists, whether certain hedge funds are more skilled activists than others and what characterizes skilled hedge fund activists has received limited attention in the literature. In this paper, we use a Bayesian estimation technique to extract hedge fund-specific skill components from announcement returns to activist campaigns and analyze their properties in the cross section of hedge fund activists. We then link our skill estimates to observable campaign characteristics and explore what differentiates skilled hedge fund activists from their peers.

The existing literature has devoted considerable time to differentiating skill from luck among various groups of money managers (including hedge funds). For hedge funds, performance evaluation is complicated by reporting biases in return data that have been associated with standard hedge fund performance databases (Aiken, Clifford and Ellis, 2013; Aragon and Nanda, 2017). In our analysis, we overcome this limitation by estimating performance of hedge fund activists with publicly observable returns to activism campaign announcements, and hence do not rely on voluntarily reported hedge fund performance data. Because cumulative abnormal announcement returns reflect the market's assessment of the expected value increase in the activist's target, our measure of skill is tightly linked to an activist's ability to create wealth for target firm shareholders in the short term. Short-term announcement effects are also a much cleaner measure of an activist's impact on a target firm compared

[1] Based on data taken from Factset's Shark Repellent (Activism) data base. We also observe a sharp rise in the number of hedge fund activists over the same period, increasing from just 21 in 2001 to 78 in 2018.

to longer holding period returns, which may be confounded by subsequent corporate or macroeconomic events.

The skill estimation technique we use in this paper adapts the Bayesian framework described by Korteweg and Sorensen (2017), who study performance persistence in private equity funds. Our estimate of skill can be thought of as a time-invariant component of cumulative abnormal announcement returns, which we attribute to a specific hedge fund activist. With these estimates, we can then study dispersion in skill across our sample of hedge fund activists and examine whether meaningful differences in hedge fund activism skill exists. The Bayesian estimation algorithm we use overcomes some of the shortcomings of a standard fixed effects regression in our setting. Especially in short panel settings, our method can generate a posterior distribution for the dispersion in hedge fund activism skill and does not rely on the empirical distribution of estimated fixed effects to analyze such dispersion.[2]

Our findings strongly support the notion of hedge fund activist-specific skill and, moreover, meaningful heterogeneity in skill across hedge fund activists.[3] The Bayesian estimation algorithm generates an estimated distribution for the variance of our hedge fund-specific skill component, which is characterized by a mean that is significantly different from zero. Stated differently, some hedge fund activists in our sample are associated with persistently higher cumulative abnormal announcement returns than other hedge fund activists. This difference in activism skills is also economically meaningful. For example, the spread in cumulative abnormal announcement returns between the hedge fund activist at the 80^{th} percentile and the 20^{th} percentile of the skill distribution is 13.10%. Our model allows us to directly extract these spreads, which can be interpreted as a measure of the difference in expected value added between hedge fund activists from our estimated distribution of skill. The main benefit of this property of our model is that unlike spreads obtained from the observed empirical distribution of cumulative abnormal announcement returns, the spreads we obtain are more informative about the true dispersion in skill, even when cumulative abnormal announcement returns are measured with considerable noise.

The estimated differences in hedge fund activists' skill also becomes apparent in out-of-

[2]Dispersion in skill becomes a parameter in our model.

[3]Note that by construction, the average of our hedge fund-specific skill measure is zero in our model. The model produces estimates of relative skill in our sample of hedge fund activists.

sample tests. To implement these tests, we first estimate hedge fund activist-specific skill from campaign announcements during the earlier half of our sample. We then regress cumulative abnormal announcement returns to campaign announcements by hedge fund activists during the later half of our sample on their previously estimated skill components. Supporting the notion that the estimated differences in skill capture a time-invariant component in cumulative abnormal announcement returns that persists over long horizons, our regression specification yields a positive and significant coefficient estimate for our skill measure. In other words, more highly skilled hedge fund activists are associated with higher cumulative abnormal announcement returns, a relationship that also holds when we measure returns out of sample. Our skill estimates can thus be beneficial for institutions who consider investing directly with a hedge fund activist as skill estimates for those activists can help inform investors' asset allocation decisions.

Similar heterogeneity appears in the performance of long-only investment strategies that follow hedge fund activists' investment choices. We form equal-weighed portfolios by investing in the same target firms as our top quintile hedge fund activists on the first trading day after those hedge fund activists file a Schedule 13D with the Securities and Exchange Commission (SEC). Depending on the specification, target firm investments remain in the portfolio for a fixed holding period of 3 to 12 months. In our data, following such a strategy generates positive risk-adjusted monthly abnormal returns of between 0.8% and 1.5%. We do not find similar outperformance when following the investment decisions of the less skilled hedge fund activists in our sample. We also do not find risk-adjusted outperformance when identifying activists' skill with average historical announcement returns. Thus our ability to differentiate high-skilled hedge fund activists from their low-skilled peers can also benefit smaller and potentially less sophisticated investors. Many investors may be too small to invest directly with a hedge fund activist and thus unable to benefit from the share price performance associated with campaign announcements. However, those investors may still achieve positive, albeit smaller, average abnormal returns when investing in the same target firms when following reports of campaign initiations.

Our estimates of skill are agnostic about whether cumulative abnormal announcement returns around an activist's investment reflect an activist's superior stock picking skills, value enhancing interventions, or both. Brav, Jiang, Partnoy and Thomas (2008) and Bebchuk, Brav and Jiang (2015) argue that improvements in target firm performance are at least partly due to activist intervention. More recently Albuquerque, Fos and Schroth (2021) estimate that 74.8% of the abnormal announcement return to hedge fund activism campaign announcements can be attributed to expected value creation and only 13.4% of the return is related to stock picking. In contrast, Cremers, Giambona, Sepe and Wang (2021) argue that hedge fund activists are effective stock pickers and are less successful in directly creating value in their targets. Adding to this debate, we analyze changes in operating performance metrics of target firms in the 5 years after activist intervention. We compare the effect of interventions by high-skill and low-skill activists on target firm operating performance with the development of the same metrics for firms in a size/book-to-market matched benchmark portfolio. The resulting abnormal operating performance measures show a clear pattern: while slightly declining or stable in the first 2 to 3 years after the activism announcement, we observe a sharp increase in target firm performance in years 4 and 5. The performance improvement is however unique to targets of highly skilled hedge fund activists and not visible for targets of their less skilled peers. Our results suggest that while campaigns of highly skilled hedge fund activists seem to be associated with improvements in target firm operating performance over longer horizons, they also highlight that when focusing on the 2 or 3 years after campaign announcements, these effects may not have materialized yet.

Complementing our analysis on operating performance, we also examine whether we can detect meaningful differences along other dimensions of hedge fund activists' campaigns. If cumulative abnormal announcement returns do contain information about the activist's intention to bring about value enhancing changes in the target firm, we would expect to observe a relation between hedge fund activists' campaign actions and those anticipated value increases. We find that skilled hedge fund activists distinguish themselves through certain characteristics of their campaigns, but not through all campaign characteristics. It is well documented in the literature that hedge fund activists are more likely to engage their target firms in merger and acquisition (M&A) activity (Greenwood and Schor, 2009; Boyson et al., 2017). While we find that a sizeable fraction of hedge fund activism campaigns result in a takeover or acquisition of the target firm within three years of the campaign's announcement, we do not find significant differences in takeover frequencies between the different activist skill groups. However, sizeable heterogeneity arises in the acquisition premium earned by existing shareholders. We find that skilled hedge fund activists are able to secure significantly higher acquisition premiums, resulting in higher value increases for existing shareholders, including the hedge fund activist.

We also examine hedge fund activists' versatility in applying different tactics throughout a campaign and their responses to target firm resistance. Working with several measures of campaign specialization, we find that skilled activists use a larger number of tactics in any given campaign and generally tend to use a broader set of tactics across their various campaigns over time. As such our findings suggest that a skilled hedge fund activist can source from a wider repertoire of tactics. Much more so than their ability to specialize in campaign styles, this is what sets them apart from their less skilled peers. We also examine target firm resistance and activist's counterresistance following the approach by Boyson and Pichler (2019). While high-skill and low-skill hege fund activists experience similar target resistance, high-skill hedge fund activists are more selective in choosing when to counterresist. This result is consistent with the notion that high-skill hedge fund activists are better at knowing when to avoid costly mistakes.

This paper make several contributions to the literature on hedge fund activism. We add to work that examines the performance of hedge fund activists, including Brav et al. (2008), Klein and Zur (2009), Greenwood and Schor (2009), Becht, Franks, Mayer and Rossi (2009), and Becht, Franks, Grant and Wagner (2017). Our decomposition of performance around the announcement of activism allows us to isolate a time-invariant hedge fund specific component in returns to activism. Estimates of this hedge fund-specific component of performance are informative about heterogeneity in skill within hedge fund activists and can be obtained with reasonable confidence from our data.

Our paper also adds to a growing literature on campaign strategies and the campaign outcomes of hedge fund activists. For example, considering M&A activity in target firms, the presence of hedge fund activists and their interventions are associated with higher takeover propensities of target firms (Greenwood and Schor, 2009), better deal terms (Boyson, Gantchev and Shivdasani, 2017; Jiang, Li and Mei, 2018), and an increased efficiency of target firms' own M&A activity (Wu and Chung, 2021). The focus of our analysis lies on contrasting these outcomes for campaigns that are initiated by more skilled hedge fund activists vs. less skilled hedge fund activists in our sample. We show that the most skilled activists primarily achieve better deal terms during target firm related M&A activity, but are not associated with a higher propensity to initiate M&A activity. Our paper also relates to a number of recent studies that analyze how differences in hedge fund activist skill measured by past experience (Boyson, Ma and Mooradian, 2022), reputation and expertise (Krishnan, Partnoy and Thomas, 2016; Johnson and Swem, 2021), and counterresistance against hostile target resistance (Boyson and Pichler, 2019) affect campaign outcomes.

Next to its contribution to the literature on hedge fund activism, our paper adds to a large literature on hedge fund managers' performance persistence, including Edwards and Caglayan (2001), Baquero, Horst and Verbeek (2005), Fung, Hsieh, Naik and Ramadorai (2008), and Jagannathan, Malakhov and Novikov (2010). In our analysis, we do not rely on voluntarily reported hedge fund performance data. In contrast, we use publicly observable returns to activism announcements to estimate performance persistence and are thus not exposed to potential reporting biases that have been associated with hedge fund performance data (Aiken, Clifford and Ellis, 2013; Aragon and Nanda, 2017). Our paper also relates to Sun, Wang and Zheng (2012) who show that hedge funds with a more unique investment strategy are associated with better subsequent performance. We show that highly skilled hedge fund activists in our sample use a larger number of tactics during the average campaign. More importantly, we also document that the most persistent positive performers employ these tactics in a more versatile way.

More generally, our paper adds to the literature on performance persistence and skill assessment in money management. Bayesian estimation methods to evaluate managerial skill have been used, amongst others, by Baks, Metrick and Wachter (2001), Pástor and Stambaugh (2002), Jones and Shanken (2005), Avramov and Wermers (2006), Busse and Irvine (2006), and Harvey and Liu (2018) in the context of mutual funds, Kosowski, Naik and Teo (2007) and Avramov, Kosowski, Naik and Teo (2011) for hedge funds, and Korteweg and Sorensen (2017) for private equity firms.

The rest of the paper proceeds as follows. Section 2 introduces the empirical model and estimation procedure. Section 3 presents our data. Section 4 reports our estimation results and discusses out-of-sample tests. Section 5 studies campaign strategies and outcomes. We provide concluding remarks in Section 6.

2 Estimating Hedge Fund Skill

2.1 Empirical model

In this section, we describe the methodology we use to estimate time invariant hedge fund-specific skill factors. Our approach is based on the idea that we can obtain estimates of hedge fund skill by observing, and learning from, the market's reaction to hedge fund activists' 13D filings. We will begin our description by introducing some useful notation. We index hedge fund activists by i, and each hedge fund may undertake one or more activist campaigns, indexed by c. For each campaign, we define the target firm's cumulative abnormal return following an activist's 13D filing as

$$y_{ic} = \alpha + \delta_t + \gamma_i + \epsilon_{ic}, \tag{1}$$

where α measures the average cumulative abnormal return across all hedge fund activist campaigns, δ_t captures a time-specific return component, γ_i captures a hedge fund activist-specific random effect, and ϵ_{ic} represents an error term.[4] While we measure the average level of performance among hedge fund activists with α, the inclusion of δ_t allows us to also capture the variation in performance that is induced by time-varying systematic shocks such as the economic cycle. We model hedge fund activist skill with the random effect γ_i, which remains constant across campaigns of a hedge fund activist. We assume that the random effect is independent of all other covariates and normally distributed with variance σ_γ^2. Stated formally,

$$\gamma_i \sim \mathcal{N}(0, \sigma_\gamma^2). \tag{2}$$

Intuitively, our hedge fund activist skill estimate γ_i measures differences in the long-term persistence of cumulative abnormal announcement returns between hedge funds. High-skill activists add more value to their target firms (high γ_i) than their low-skill peers (low γ_i).

The degree to which skill differs across hedge fund activists is captured by the estimated variation of the random effect, σ_γ^2. When σ_γ^2 is small, all hedge fund activists either possess similar levels of skill, or potential skill differences between hedge fund activists do not con-

[4]The abnormal returns y_{ic} represent returns relative to our benchmark model. We use the market model, a market-adjusted model, and the Fama-French 3-Factor model as benchmarks throughout our analysis.

tribute much to the observed variation in cumulative abnormal announcement returns. In contrast, when σ_γ^2 is large, heterogeneity in hedge fund activist skill prevails and will let us account for some of the observed variation in cumulative abnormal announcement returns.

We could have also modeled hedge fund activist skill as a fixed effect. However, as noted by Korteweg and Sorensen (2017), fixed-effect estimates are less precise in short panels, and the true variation in fixed-effect estimates can be significantly confounded by the standard errors of the fixed-effects estimation. When modeling hedge fund activist skill with a random effect, we treat the variance of the random effect as a model parameter, and are hence much better equipped to detect true dispersion in the estimate of our skill component.[5]

The error term ϵ_{ic} captures a campaign-specific idiosyncratic return component and is normally distributed:

$$\epsilon_{ic} \sim \mathcal{N}(0, \sigma_\epsilon^2). \tag{3}$$

It is independent and identically distributed across campaigns c, across activists i, and over time. Together, the random effects γ_i and the error terms ϵ_{ic} determine the covariance structure of the model. With our assumptions, the total variance of the cumulative abnormal announcement return y_{ic} can be written as

$$\sigma_y^2 = \sigma_\gamma^2 + \sigma_\epsilon^2 \tag{4}$$

where, as described before, σ_γ^2 measures the variation in hedge fund activist skill and σ_ϵ^2 measures the variation in the model's error term. Last, we can define a signal-to-noise ratio as

$$S_\gamma = \frac{\sigma_\gamma^2}{\sigma_\gamma^2 + \sigma_\epsilon^2}. \tag{5}$$

The signal-to-noise ratio quantifies the proportion of the variation in cumulative abnormal announcement returns that is attributable to the variation in hedge fund activism skill, and thus allows us to gauge how suitable the data is to detect skill differences for hedge fund activists. Stated differently, higher values of S_γ imply that less variation in cumulative

[5]The associated costs of this modeling choice is that we need to make additional distributional assumptions and assume that the random effects are independent of the other covariates.

abnormal announcement returns is due to noise (measured by the error term ϵ_{ic}), and that we will be able to identify high-skill hedge fund activists with higher accuracy.

2.2 Estimation procedure

We estimate Equation (1) with a Bayesian estimator (Rossi, Allenby and McCulloch, 2012). In particular, we use a Markov Chain Monte Carlo (MCMC) algorithm to construct the joint posterior distribution of the parameters in our model, given the observations in our data (Korteweg, 2013; Korteweg and Sorensen, 2017). In this section, we briefly describe the specific elements of our estimation procedure. A more comprehensive description is provided in Online Appendix A.

The main objective of our estimation procedure is to estimate the parameter vector $\theta \equiv (\beta, \sigma_\gamma^2, \sigma_\epsilon^2)$, conditional on observing cumulative abnormal announcement returns y_{ic} of the hedge fund activists' campaigns, and our distributional assumptions for σ_γ^2 and σ_ϵ^2, which we defined in Equations (2) and (3). The vector β includes the parameters for the average cumulative abnormal return (α) and all time-specific return components (δ_t).

To define the joint posterior distribution of the model parameters, we first have to augment the parameter vector θ with latent values for the hedge fund-specific random effects γ_i. The joint posterior distribution of θ is then defined as $f(\theta, \{\gamma_i\}|Data)$.

The MCMC algorithm produces a set of draws from this joint posterior using the Gibbs sampling technique (Geman and Geman, 1984; Gelfand and Smith, 1990; Korteweg, 2013), which effectively splits our joint posterior distribution of θ into three conditional distributions: (1) the distribution of the variance of the campaign-specific error term (σ_ϵ^2) and beta coefficients (β) $-$ $f(\beta, \sigma_\epsilon^2|\sigma_\gamma^2, \{\gamma_i\}, Data)$; (2) the distribution of hedge fund-specific latent random effects (γ_i) $-$ $f(\{\gamma_i\}|\theta, Data)$; and (3) the distribution of the variance of the hedge fund-specific random effect (σ_γ^2) $-$ $f(\sigma_\gamma^2|\beta, \sigma_\epsilon^2, \{\gamma_i\}, Data)$. We sequentially sample from these three distributions, update our beliefs with each draw, and iterate the sampling cycle 100,00 times. The resulting sequence of parameter draws forms a Markov chain whose stationary distribution is exactly the joint posterior $f(\theta, \{\gamma_i\}|Data)$.

Given a sample of draws from this stationary distribution of the Markov chain, we can then characterize the marginal posterior distributions of the model parameters $f(\theta|Data)$ and the hedge fund-specific random effect $f(\{\gamma_i\}|Data)$. In particular, we use every 10^{th} draw from the posterior distribution over our sampling cycle to characterize the marginal posterior distributions of model parameters θ and $\{\gamma_i\}$. Stated differently, the MCMC algorithm produces a distribution for each hedge fund-specific random effect γ_i, and the means of these distributions form our estimates of each hedge fund activist's level of skill. Before we present estimation results for our model, in the next section we briefly introduce our main data sources.

3 Data

3.1 Data sources

We use FactSet's Shark Repellent database to construct our sample of hedge fund activism campaigns. Restricting ourselves to the period from 2001 to 2018, our initial sample consists of 7,456 activism events with non-missing announcement dates and available data on the type of activist. We then use FactSet's activist type to identify hedge fund activists (activist type: *Hedge Funds*) and are left with 3,661 events that were initiated by this particular activist type during our sample period.

Next, we compile stock return data for the campaigns' target firms. To do so, we first require that an activist event is announced with a Schedule 13D filing. FactSet also includes activism events that are associated with proxy fights or other publicly communicated campaigns, and we exclude these from our analysis. Second, we remove activism events that are initiated by multiple hedge funds. We do so in order to be able to clearly attribute the market reaction in a target firm's share price to a single activist. Third, we match target firms to the Center for Research in Security Prices (CRSP)'s daily stock return file using a 6 digit CUSIP identifier that is also available in FactSet. Imposing these additional conditions, we are left with 2,054 hedge fund activist campaigns for which we have the requisite stock return data of the campaign targets.

Figure 1 shows the number of hedge fund activist campaigns in our sample from 2001 to 2018. To better compare our sample to previous studies, we also include the yearly campaign count from an updated sample that uses the same data collection procedure and estimation methods as in Brav et al. (2008) and Brav, Jiang, Kim et al. (2010).[6] Overall, our event

[6]See `https://faculty.fuqua.duke.edu/~brav/HFactivism_March_2019.pdf` (retrieved 08/10/2021).

count is slightly lower than that in the benchmark sample, which is an artefact of requiring a Schedule 13D filing for each campaign. The differential is larger in the earlier part of the sample (before the financial crisis) and much smaller in the later part of the sample (after the financial crisis). The time-series patterns in the two samples are very similar, with hedge fund activism rising sharply between 2004 and 2007, and then dropping significantly during the financial crisis years of 2008 and 2009. We also observe similar patterns for the number of unique hedge fund activists in both our sample and the benchmark sample. For brevity, we report these results in Online Appendix Figure OA1.

All stock return data, as we have mentioned above, comes from CRSP's daily stock return file. We augment our daily return series with return series of the Fama-French 3 factors, which we obtain from Kenneth French's data library.[7] From CRSP, we also obtain data on the value-weighed total return index as an alternative proxy for the market portfolio.

Last, we compile a data set on the existence of certain regulatory filings in close proximity to the activism campaign announcement to analyze campaign outcomes. For example, we identify activity related to mergers and acquisitions or tender offers within three years of the filing of a campaign's initial Schedule 13D. Such activity can be identified with information statements for merger transactions or acquisitions (DEFM14C), definitive proxy statements relating to a merger or acquisition (DEFM14A), and third party tender offer announcements (Schedule TO-T). We download all of these publicly available regulatory filings from the SEC's Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) database.

3.2 Target firm cumulative abnormal announcement returns

The dependent variable in our primary model, described by Equation (1), is a cumulative abnormal announcement return, which we observe for target firms around the initiation of a hedge fund activism campaign. Following the literature, we use the date of an initial Schedule 13D filing by a hedge fund activist as the event date (see e.g. Brav et al., 2008; Clifford, 2008; Greenwood and Schor, 2009; Klein and Zur, 2009). Because the SEC only requires an activist to file a 13D within 10 days of acquiring a 5% stake in the target firm, we analyze different event windows. Our shortest event window is a three-day window, defined from $t-1$ to $t+1$, where $t=0$ is the event date. We also analyze windows from $t-10$ to

[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$t+1$ and $t-10$ to $t+5$ to capture situations in which the market might acquire information about the event prior to the actual filing date, i.e. within the 10-day grace period. Last, to be able to also detect post-announcement drifts in the data, we study an event window from $t-20$ to $t+20$.

For our main analysis, we use the Fama-French 3-Factor model to compute expected returns. The model is estimated within a 200-day estimation window, ranging from $t-220$ to $t-21$. In our robustness analysis, we also use the market model and the market-adjusted model as alternative approaches to compute expected returns. The value-weighted CRSP total return index serves as the proxy for the market portfolio in both of these settings.

We define a cumulative abnormal announcement return for each hedge fund activist i's campaign c over the event period from t_1 to t_2 as:

$$CAR_{ic}(t_1 t_2) = \sum_{t=t_1}^{t_2} AR_{ict} \tag{6}$$

where AR_{ict} is the corresponding abnormal announcement return of the target firm on day t, which we compute using expected returns from our benchmark model (the Fama-French 3-Factor model in our main analysis).

Panel A of Table 1 shows the distribution of cumulative abnormal announcement returns in our sample. We separately report the returns for our four event windows. The first row shows average cumulative abnormal announcement returns for the 3-day window (from $t-1$ to $t+1$) around the 13D announcement. On average, a campaign announcement by a hedge fund activist in our sample generates a 3-day cumulative abnormal return of 3.54%. Across campaigns, we find considerable heterogeneity in those returns. More than 25% of all campaigns are associated with a negative 3-day cumulative abnormal return, with abnormal returns lower than -14.88% for 1% of the campaigns. At the same time, the median 3-day cumulative abnormal announcement return is 2.08%, and 1% of the campaigns realize an abnormal return in excess of 34.38%. Very similar patterns emerge for our longer event windows.

In Panel B of Table 1, we focus on the differences between hedge fund activists; i.e., we report the distribution of cumulative average abnormal announcement returns.[8] The

[8]Cumulative average abnormal announcement returns are computed for each hedge fund activist i by averaging cumulative abnormal announcement returns over all N campaigns of the activist:

specification in the second column, for example, shows that the average hedge fund activist, across their campaigns, generates an average cumulative abnormal announcement return of 4.55% over a 12-day window (from $t-10$ to $t+1$) around the 13D announcement. There is, however, also significant variation in these average returns. For the same specification, more than 25% of the hedge fund activists in our sample generate negative announcement returns across their campaigns, on average. At the same time, more than 10% of our hedge fund activists generate announcement returns in excess of 15%, on average. We observe similar variation in average cumulative abnormal announcement returns between hedge fund activists for our other event windows.[9] While our summary statistics in Panel B differ from those in Panel A only by the different weighing scheme we use to compute averages, they reinforce the point that the market's average reaction to hedge fund activism differs substantially between different hedge fund activists. As such, we view our univariate results as providing a first necessary condition for our attempt to estimate hedge fund-specific skill effects, which we will turn to in the next section.

4 Hedge fund-specific skill

4.1 On the existence of skill

One benefit of estimating our model with a Bayesian estimator is that it yields an estimate of the standard deviation of the hedge fund-specific random effect, σ_γ. This estimate is useful in that it allows us to gauge the extent to which we can detect dispersion in hedge fund activist skill from our data. Or stated differently, if our estimate of the standard deviation of the hedge fund-specific random effect is significantly different from zero, our data supports the idea that some hedge fund activists are persistently associated with higher cumulative abnormal announcement returns. We would than consider these activists to be more skilled.

Panel A of Table 2 reports our estimates of the standard deviation of the hedge fund-

$$CAAR_i(t_1 t_2) = \frac{1}{N}\sum_{c=1}^{N} CAR_{ic}(t_1 t_2). \tag{7}$$

[9]These patterns are not driven by the choice of our benchmark model for the computation of expected returns. We obtain similar results when using our alternative benchmarks and report these in Online Appendix Table OA1.

specific random effect σ_γ and the standard deviation of the error term σ_ϵ of Equation (1). Each column reports estimates that relate to a specific event window that we use to compute our cumulative abnormal announcement returns. In all columns, we use the Fama-French 3-Factor model to obtain expected returns. Focusing on the 12-day event window (from $t-10$ to $t+1$), our estimate of σ_γ is 0.154, which is highly statistically significant. Figure 2 shows the corresponding distribution of our estimate of σ_γ, and the number that we report in Panel A of Table 2 represents the mean of this estimated posterior distribution. The fact that our estimate of σ_γ is significantly different from zero suggests that in our sample of hedge fund activists, there is dispersion in skill across hedge funds, and some hedge funds are persistently associated with higher cumulative abnormal announcement returns when filing a 13D than their peers. These results are not specific to the 12-day event window. Similar results emerge as we observe the other columns of the table. As we consider longer event windows, cumulative abnormal announcement returns become noisier and hamper our ability to extract clear signals of hedge fund activism skill. This is evident in the increasing magnitudes of our estimates of the standard deviation of the error term σ_ϵ.

We also verify that the ability to identify hedge fund skill is not an artifact of our FactSet sample and the classification of hedge fund activists by the data provider. Using the extended sample of Brav et al. (2008) ending in 2016, Appendix Figure A1 shows that we are able to detect skill in both samples (Panel A), and that we can detect skill when campaign announcements are based on Schedule 13D filings and other news outlets (Panel B).[10]

Another noteworthy feature of our approach is that it allows us to estimate differences in cumulative abnormal announcement returns, or value added to the target, between more skilled and less skilled hedge fund activists. A necessary condition for this exercise is that we obtain a non-zero estimate of the variance of the distribution of hedge fund activist-specific skill, which as we discussed above, is the case in our sample. Then, the value added, or persistent spread in cumulative abnormal announcement returns between any two hedge fund activists on the skill distribution of γ can be calculated from our estimated posterior of γ. For example, for the setting described in Column 1 of Table 2, i.e. our 3-day event window, the persistent spread in cumulative abnormal announcement returns between the hedge fund activist at the 80^{th} percentile and the 20^{th} percentile of the skill distribution is 13.10%. The

[10]We thank Alon Brav for sharing his data with us.

terms $q_\gamma(80\%)$ and $q_\gamma(20\%)$ in the table denote the values of the skill distribution evaluated at the respective percentile. That spread is 18.60% for our 12-day event window (Column 2). Intuitively, we think of this spread as a proxy of the average value added (to a target) by the marginal top quintile hedge fund activist relative to the marginal bottom quintile hedge fund activist.[11] We report this spread and two other spreads (75^{th} percentile vs 25^{th} percentile and 90^{th} percentile vs 10^{th} percentile) in Panel B of Table 2.

It is important to note that the spreads that we calculate above are not the same as spreads that we could easily obtain from the distribution of cumulative abnormal announcement returns. The spreads we calculate are a much better measure of differences in persistent hedge fund-specific skill than comparable spreads of the distribution of cumulative abnormal announcement returns. This is best explained with an example. Consider the case when cumulative abnormal announcement returns are measured with considerable noise (i.e., σ_ϵ is large) but the variation in the hedge fund-specific random effect is low (i.e., σ_γ is small). Our estimated spreads would be low because the posterior distribution of our hedge fund-specific random effect has a small variance. At the same time, since σ_ϵ is large, we would still obtain sizeable spreads from the distribution of cumulative abnormal announcement returns (overwhelmingly due to noise), which would significantly overstate the true difference in the persistent value add of different hedge fund activists.

4.2 Out of sample performance

4.2.1 Cumulative abnormal announcement returns

In the previous section, we have documented significant dispersion in hedge fund activism skill. In this section, we examine whether we can use hedge fund-specific skill estimates to predict future announcement returns to activism campaign initiations. To explore this question, we proceed in two steps. First, we estimate hedge fund-specific random effects γ_i using only data from 2001 to 2012. We label this period our estimation window. While we can obtain skill estimates for each hedge fund activist with one or more campaigns during our estimation window, we only keep those hedge funds for which we observe at least two

[11] The marginal top quintile hedge fund activist is the first (or lowest-skilled) fund in the top skill quintile. Similarly, the marginal bottom quintile hedge fund activist is the last (or highest-skilled) fund in the bottom skill quintile.

campaigns, one during the estimation phase, and one thereafter. A total of 103 activists fulfill this criteria. Second, we examine the relationship between cumulative abnormal announcement returns and our skill estimates in a subsequent period, which includes the years from 2013 to 2018. We label this period the validation phase. Stated differently, we use data from the validation phase to regress cumulative abnormal announcement returns on our hedge fund-specific skill estimates and time fixed effects. Skill estimates are exclusively obtained from data from the estimation phase.

If our skill estimates do capture long-term persistence in cumulative abnormal announcement returns, we would expect to see positive coefficient estimates for our skill measure in the aforementioned regression specification. We report our results in Table 3. This analysis is based on a total of 450 campaigns initiated by 103 hedge fund activists, and we focus our discussion on results that we obtain when measuring cumulative abnormal announcement returns over a 12-day window (from $t-10$ to $t+1$) against returns from the Fama-French 3-Factor model. Despite our small sample, we find a positive and significant (at the 10 percent level) relationship between cumulative abnormal announcement returns out of sample. Our point estimate of 0.863 implies that a one standard deviation increase in our skill measure is associated with an increase in future cumulative abnormal announcement returns of 4.77 percentage points (0.863×0.05532). The magnitude of this effect is economically meaningful, and compares to, for example, a 13.54% inter-quartile range of the distribution of cumulative abnormal returns for the same 12-day event window.

In further analysis, we verify that our results are robust to controlling for an activist's annual campaign frequency and target firm characteristics such as book-to-market ratios, sales, return on assets, cash flow, financial leverage, cash, dividend yield, and research and development (R&D) expenses. We report these specifications in columns 2 - 4 of Table 3.

In conclusion, our methodology is not only capable of characterizing the distribution of hedge fund activist-specific skill in the data, but also allows us to identify those hedge funds that persistently generate higher cumulative abnormal announcement returns when initiating their campaigns. Our methodology may thus also benefit investors who are considering directly investing with hedge fund activists and have the opportunity to select between different competing entities.

4.2.2 Calendar-Time Portfolio Regressions

Can knowledge about hedge fund activist-specific skill be exploited by investors who do not directly invest with a hedge fund activist? To answer this question, we examine whether investors who learn about skilled hedge fund activists' investments by observing their Schedule 13D filings can generate risk-adjusted outperformance when trading on this information.

We begin by analyzing the performance of long-only investment strategies that follow hedge fund activists' investment choices. The information set we rely on includes estimates of hedge fund activists' levels of skill and Schedule 13D filings they file with the SEC. Based on this information, we form equal-weighed portfolios by investing in the same target firms as our top quintile hedge fund activists on the first trading day after those hedge fund activists file a Schedule 13D. We keep each target firm in the portfolio for a fixed holding period that, across our various specifications, ranges from 3 months to 12 months. When a skilled hedge fund activist announces a new investment, we include the new target firm in our portfolio and rebalance the other positions accordingly to maintain the equal weighting of all portfolio investments. Similarly, at the end of an investment's holding period, we remove the target firm from the portfolio and rebalance the remaining positions.

The portfolio formation year is 2002. Initially, we obtain skill estimates to identify skilled hedge fund activists with campaign announcement data from 2001. For all subsequent calendar years, we estimate skill with an expanding estimation window that includes campaigns between 2001 and the year prior to the respective investment year. To select investments in firms targeted by top quintile activists in 2018, for example, we estimate skill with campaign data from 2001 to 2017. The result of following this strategy is that we observe out-of-sample returns of a dynamic portfolio of investments in firms that are targeted by the top quintile of hedge fund activists based on the dynamically updated learning of their skill.

We measure whether our investment strategy is able to generate abnormal returns (α) against two standard benchmarks: the Fama French 3-factor model and the Fama French 5-factor model. Panel A of Table 4 presents estimation results of abnormal performance for monthly portfolio returns against our two benchmarks and for holding periods ranging from 3 months to 12 months. Mimicking investments of highly skilled hedge fund activists generates positive and significant α across all of our risk adjustment models as well as for the various holding periods we consider in our analysis. Stated differently, the results in Panel A support the conjecture that knowing our skill estimate (γ) can be used to predict out-of-sample outperformance by our top quintile hedge fund activists.

In terms of their economic magnitudes, our results are sizeable. Focusing on α estimates for the Fama French 3-Factor model and a 3-month holding period, our strategy generates a positive monthly outperformance of 1.5% (significant at the 5% level). This result translates to an annualized α of 19.56%. Other holding periods result in similar effects. For the 6-month holding period, we estimate a monthly α of 1.4% (still significant at the 5% level). Working with 9- and 12-month holding periods results in slightly lower estimates of monthly α, now in the order of 0.8% and still significant at the 10% and 5% level, respectively. The annualized α for these longer holding periods still amounts to 10.03%. Using the Fama French 5-Factor model as our benchmark produces very similar results. In summary, investing in targets of top quintile hedge fund activists generates statistically significant abnormal returns of 10% - 20% per year out of sample.

How important is the hedge fund-specific skill estimate we introduce in this paper for the outperformance of our mimicking portfolio? We examine this question with two analyses in Panels B and C of Table 4. The first piece of evidence we present addresses the contribution of our skill estimate as a signal for portfolio formation. Instead of relying on our somewhat involved measure of skill, we implement a strategy that relies on a simple measure of past performance. In Panel B of Table 4, we report results of the out-of-sample outperformance of a strategy that identifies high-skilled hedge fund activists with historical average cumulative abnormal announcement returns. Using the same general setting as in our previous analysis, investing in target firms of hedge fund activists with high average past CAARs yields very different results. Looking across the different holding periods and the various risk adjustment models in the first line of the panel, none of our estimates for outperformance are statistically significant. This finding highlights the ability of our skill estimate to identify a persistent component in post-announcement investment returns that is much harder to capture with simple sorting of historical returns.

In our second analysis, we investigate whether the out-of-sample outperformance that we report in Panel A results from exploiting the distribution of our skill estimate. If the information in the distribution of our skill estimate is relevant to the performance of our portfolio, mimicking investments of low-skilled hedge fund activists should not yield similar outperformance results. In Panel C of Table 4, we present estimates of risk-adjusted α for portfolio returns from investing in targets of our bottom quintile hedge fund activists.

Similar to our previous findings in Panel B, none of our estimates are statistically significant across the different holding periods and the various risk adjustment models. Economically the estimated monthly α coefficients are much lower than those reported for our high-skill mimicking strategy in Panel A. Focusing again on α estimates for the Fama French 3-Factor model and a 3-month holding period, we now obtain a positive but insignificant monthly α of 0.5% or 6.17% when annualized. For the 12-month holding period, our estimate of monthly α is 0.2% (again insignificant) or 2.43% annualized. These magnitudes are in stark contrast to the outperformance of 19.56% and 10.03% that we document for the same holding periods and risk adjustment models when mimicking investments of our high-skill hedge fund activists.

In conclusion, the previous analyses reveal that our skill measure plays a crucial part in the out-of-sample performance of our mimicking portfolio strategy. Simple alternative methods of identifying high-skill hedge fund activists or following investments of low-skill hedge fund activists do not result in similar out-of-sample outperformance. These findings are also robust when using buy-and-hold abnormal returns instead of our calendar-time portfolio approach.[12]

4.3 The speed of learning

In this section, we study another important property of the model, i.e. how fast we can learn about skill as our data expands. To do so, we rely on the concept of the signal-to-noise ratio S_γ, introduced in Section 2. A higher signal-to-noise ratio implies that our cumulative abnormal announcement returns are more informative about the dispersion in the hedge fund-specific random effect, which serves as our proxy for persistent hedge fund activist skill. We report estimated signal-to-noise ratios for our different event windows in Table 5. Except for the longest event window of 41 days in Column 4, all shorter event windows result in high signal-to-noise ratios, which range from 0.44 to 0.49. Comparing the magnitudes of our signal-to-noise ratios to those obtained by Korteweg and Sorensen (2017) for their sample of private equity firms suggests that our sample provides a reasonable setting to identify skilled hedge fund activists.

[12] We report results of arithmetic and geometric average buy-and-hold returns in Appendix Table A1. Investors can generate positive buy-and-hold abnormal returns by mimicking investment decisions of skilled hedge activists, not in every year of our sample, but at least on average.

The signal-to-noise ratio can also be used to obtain estimates of the speed of learning about the persistent differences in hedge fund activist skill. Intuitively, when cumulative abnormal announcement returns are more informative about the hedge fund-specific skill component, we will learn about them at a greater pace with the arrival of each new campaign. Or stated differently, the higher the signal-to-noise ratio, the more certain we are that our estimated level of skill accurately reflects the true level of skill provided we are able to observe a fixed number of campaigns. To formalize this idea, we use the setting described in (Korteweg and Sorensen, 2017) and assume that the belief about the skill of hedge fund activist i (γ_i) after observing N campaigns is $\gamma_i \sim \mathcal{N}(\gamma_{i,N}, \sigma^2_{i,N})$. After observing the cumulative abnormal announcement return of the next campaign $N+1$, the updated belief is $\gamma_i \sim \mathcal{N}(\gamma_{i,N+1}, \sigma^2_{i,N+1})$, where

$$\gamma_{i,N+1} = S_\gamma \times [y_{i,N+1} - X'_{i,N+1}\beta] + (1 - S_\gamma) \times \gamma_{i,N} \tag{8}$$

and

$$\sigma^2_{i,N+1} = (1 - S_\gamma) \times \sigma^2_{i,N} \tag{9}$$

Equation (8) is a combination of two terms, weighted by the signal-to-noise ratio. The first term captures the new information about γ_i, given the observed cumulative abnormal announcement return of the subsequent campaign $N+1$. The second term represents our prior belief about γ_i. The higher the signal-to-noise ratio, the more weight is allocated to the information in the newly observed cumulative abnormal announcement return, resulting in a more pronounced update of our belief about γ_i. Equation (9) shows the updated dispersion in our belief about γ_i, which is decreasing in the signal-to-noise ratio. Hence, the dispersion in our belief about γ_i declines at a faster pace with increasing signal-to-noise ratio. Stated differently, a larger signal-to-noise ratio allows us to learn faster about the true value of γ_i.

With these concepts at hand, we can define the probability that hedge fund activist i's true value of skill, γ_i, lies above the P^{th} percentile of the distribution of γ, conditional on observing N cumulative abnormal announcement returns to campaigns of hedge fund activist i, and N cumulative abnormal announcement returns of the marginal P^{th} percentile hedge fund activist up until that same point in time. This probability can be written as

$$Pr\left[\gamma_i \geqslant q_\gamma(P^{th}) \middle| \frac{1}{N}\sum_{n=1}^{N} y_{i,n} \geqslant Q_N\right] \tag{10}$$

where $q_\gamma(P^{th})$ is the marginal P^{th} percentile activist hedge fund's γ_i, the term $\frac{1}{N}\sum_{n=1}^{N} y_{i,n}$ is the average observed cumulative abnormal announcement return associated with hedge fund activist i over N past campaigns, and Q_N is the average observed cumulative abnormal announcement return of the marginal P^{th} percentile hedge fund activist with N past campaigns. We provide further details on how to construct this probability in Online Appendix B. Intuitively, the above probability converges to $1-P$ as σ_γ converges to zero; i.e., the probability that a hedge fund activist with a cumulative abnormal announcement return above the P^{th} percentile can be expected to have a cumulative abnormal announcement return in the same percentile in the next campaign is expressed as $1-P$. As cumulative abnormal announcement returns become more informative about γ_i (i.e., the signal-to-noise ratio increases), the aforementioned probability increases above $1-P$, and converges to 100% as the signal-to-noise ratio converges to 1.

Figure 3 shows the probability described by Equation (10) for our 4 different event windows as a function of the number of completed campaigns N. The figure suggests that it only takes a handful of observed campaigns for us to be able to identify skilled hedge fund activists, and that we can identify those skilled activist with a high degree of certainty. For example, focusing on the 12-day event window, it only takes about 5 campaigns before we can identify with more than 80% certainty those hedge fund activists that we expect to have cumulative abnormal announcement returns in the top quintile. We obtain similar speeds of learning for the other event windows. The only exception is the 41 day event window, with which we can estimate the hedge fund-specific random effect less precisely, and hence observe much slower speeds of learning relative to the other event windows.

5 Understanding activism skill

Thus far, we have documented significant differences in announcement returns to campaigns of high-skilled versus low-skilled hedge fund activists. Do these differences reflect different campaign styles, different campaign tactics, or even different campaign outcomes? In a rational market, to warrant higher average announcement returns, campaigns of the high-skilled activist have to be more value enhancing on average. In this section, we shed light on these questions by examining campaign characteristics that are considered contributing factors to enhancing shareholder value. In particular, in the next five subsections, we analyze whether differences in hedge fund activist skill are associated with heterogeneity in the likelihood that a campaign results in a merger or acquisition of the target, heterogeneity in the associated acquisition premium that is offered to target shareholders, heterogeneity in target performance, heterogeneity in the degree of specialization with respect to hedge fund activist campaign tactics, and heterogeneity with respect to the presence of pre-event, activism-friendly institutional investors.

5.1 Probability of takeover bid

We begin our analysis by examining the relationship between activism skill and the propensity of engaging the target firm in mergers or acquisitions. Starting with Greenwood and Schor (2009), a growing literature has documented that hedge fund activists are more likely to have their target firms' ownership change in a takeover than other activists. Whether there exits heterogeneity in these takeover propensities within the group of hedge fund activists is still largely unexplored.

To identify M&A activity, we analyze all instances in which a target firm files one of the following two documents: a definitive proxy statement relating to a merger or acquisition (DEFM14A); or a Schedule TO-T, which must be filed when an acquiror makes a tender offer to acquire more than 5% of the target firm's shares. For each activism skill quintile, we then compute the fraction of campaigns that are associated with M&A activity, and summarize our analysis in Figure 4. The left part of the figure shows the fraction of campaigns that are associated with M&A activity, within 1, 2, and 3 years of the activist's filing of a Schedule 13D, for each skill quintile.

No clear pattern emerges. Between 17.77% and 25.66% of the campaigns are associated with M&A activity within 1 year of the activist's 13D filing date. Up to 34.09% of campaigns are associated with M&A activity within 3 years of the activist's 13D fling date, and the majority of campaigns that are associated with M&A activity are associated with those activities within the first year of activist intervention. Across all time horizons, as we move from low-skill to high-skill quintiles, the fraction of M&A-related campaigns first rises, is highest in the 3rd and 4th quintiles, and then gradually declines to levels that are comparable to the lowest-skill quintile. The most remarkable difference in the fraction of campaigns that are associated with M&A activity between the lowest- and the highest-skill quintile is the variation between the three horizons within each quintile. 85.45% of campaigns that are associated with M&A activity for the highest-skill quintile are initiated within the first year after the 13D filing, while the same number for activists in the lowest-skill quintile is 63.63%.

In the middle part of Figure 4, we further distinguish between merger announcements (DEFM14A) and tender offer announcements (SC TO-T). This figure is based on our 3-year horizon. Two observations are noteworthy. On average, the propensity to engage in strategies that involve mergers and acquisitions is about 4 times as high as the propensity to engage in comparable strategies that involve tender offers. While the pattern for mergers is roughly similar to what we found in the full sample (see the left part of Figure 4), a different pattern emerges for tender offers. The propensity to engage in tender offers decreases from low- to high-skill activists, and low-skill activists are more than 2.5 times as likely to engage in strategies that involve tender offers than their high-skilled peers.

In conclusion, while we find that a sizeable fraction of hedge fund activists in our sample force their target firms into a takeover, this strategy seems to be equally applied by low- and high-skill hedge fund activists. Hence, the superior performance of high-skill hedge fund activists cannot primarily stem from the market's expectation about takeover probabilities.

5.2 Acquisition premium

Next, and related to the previous section, we examine acquisition premiums of corporate control transactions. Boyson et al. (2017) show that activist interventions lead to substantially higher acquisition premiums, but do not address the potential for heterogeneity in those premiums in the cross section of hedge fund activists. To do so, we hand collect acquisition offers from merger-related definitive proxy statements (DEFM14A). When an offer is a stock offer or consists of a cash and stock component, we compute the equivalent cash value of the offer using the dollar price per share imputed from the agreed exchange ratio and the target's stock price. In most cases, this dollar price per share is provided in the regulatory filing. If a dollar price per share is not available in a filing, we impute it from the exchange ratio and the target's observed stock price as of the end of the filing date.[13] We then follow Boyson et al. (2017) and define the acquisition premium on a per-share basis as the offer price relative to the target's stock price 25 days prior to the merger announcement. Our final sample of merger premiums consists of 541 target firms, and the average acquisition premium is 30.71%.

When we compute the average acquisition premium by activist skill quintile, a very distinct pattern emerges, which we report in the right part of Figure 4. The average acquisition premium is lowest for the lowest-skill quintile, amounting to 17.03%. It then monotonically increases, and reaches its peak at 44.44% for the highest-skill quintile. The difference in the average acquisition premium between the lowest- and the highest-skill quintile, 27.42%, is significant at the 1% level. Our results are consistent with the idea that high-skill hedge fund activists are better able to generate sizeable gains for target shareholders during the M&A process relative to their low-skilled peers.

Overall, our results indicate that higher cumulative abnormal returns to campaign announcements of high-skill hedge fund activists are not driven by their higher propensity to engage their target firms in M&A activity. As we have documented in the previous section, the propensity of such activity shows little variation across hedge fund activist skill quintiles. Once highly-skilled hedge fund activists do engage in M&A activity; however, the resulting acquisition premiums offered to target shareholders are significantly higher, hence implying a higher value added for target shareholders. As a consequence, in anticipation of a favorable M&A outcome, these differences in acquisition premiums will contribute to the higher cumulative abnormal returns to campaign announcements of high-skill hedge fund activists.

5.3 Long-term Operating Effects of Interventions

Evidence on the effect of activist interventions on target firm performance has played a significant role in the discussion of the merits of activism. Several studies have documented ex-post performance improvements in target firms over shorter horizons and longer horizons of up to five years (Brav et al., 2008; Bebchuk et al., 2015). On the other hand, examining similar post-performance horizons, some papers fail to find significant improvements in

[13] In Appendix Figure A2, we report statistics on cash, stock, and combined cash/stock offer types by skill quintile. On average, 89.65% of the offers in our sample are cash offers, and there is little variation in offer types between the different activist skill quintiles.

operating performance for target firms (Klein and Zur, 2009; DeHaan et al., 2019). Adding to this literature, we analyze long-term operating performance in the context of our hedge fund skill estimates. In particular, we compare various measures of operating profitability for target firms across the skill distribution of hedge fund activists.

For our analysis, we construct metrics of operating profitability (PM_{it}) for all firms that remain independent for at least three years after campaign initiation. We then track these metrics over 9 years from 3 years prior (t = −3) to 5 years after (t = +5) the year of a hedge fund activist's filing of its initial Schedule 13D (t = 0). In each year of these 9 years, we calculate an abnormal profitability metric (APM_{it}) as follows:

$$APM_{it} = PM_{it} - PM_{it}^{b} \tag{11}$$

where PM_{it}^{b} is the equal-weighted operating profitability metric for a size/book-to-market benchmark portfolio for target firm i in year t. To form our benchmark portfolios, we first partition the universe of all firms listed on the NYSE, AMEX, and NASDAQ into 14 size-based reference portfolios.[14] Next, we partition each size portfolio into five book-to-market quintiles. The result is a total of 70 reference/benchmark portfolios, which we compute for each year of our sample period. We provide a more detailed description of the construction of our reference portfolios in Appendix D.

In the last step, we separately construct average abnormal profitability metrics for each of our activist skill quintiles:

$$\overline{APM}_{mt} = \frac{1}{n_m} \sum_{i=1}^{n_m} APM_{it,i \in m} \tag{12}$$

where $\overline{APM}_{mt}$ is the average abnormal profitability metric (in year t) for all campaigns that are initiated by hedge fund activists in the mth skill quintile in year t. $APM_{it,i \in m}$ is the individual abnormal profitability metric of activist i in year t, while activist i belongs to the mth skill quintile. n_m is the number of campaigns initiated by all activists of the mth skill quintile in year t.

[14] We form size deciles based on the market capitalization of all NYSE firms and then divide the smallest decile into quintiles based on the market capitalization of all firms in the decile, irrespective of their exchange. We follow this approch because approximately 50% of all firms fall in the smallest size decile. In total, this results in our 14 size-based portfolios.

The profitability measures we use in our analysis are return on assets (ROA), return on equity (ROE), and return on invested capital (ROIC).[15] In Figure 5, we report average abnormal profitability metrics for our highest and lowest skill quintiles along with their 90% confidence intervals. All measures are shown from 3 years before to 5 years after campaign initiation.

Panel A of Figure 5 shows the average abnormal return on assets ($\overline{ROA}_{mt}$) for firms targeted by high-skill activists (left) and low-skill activists (right). For targets of high-skill activists, $\overline{ROA}_{mt}$ is declining on average. However, this decline is not significantly different from the patterns we observe for targets of low-skill activists in the three years leading up to the campaign. The average abnormal performance of targets of low-skill activists is negative but relatively stable during the same period. In the presence of the activist, we find that $\overline{ROA}_{mt}$ stabilizes for targets of high-skill activists over the first three years, but this pattern is again not statistically different from that of low-skill activist targets. In years 4 and 5 post-activism intervention, we observe a pronounced improvement in average abnormal ROA among firms targeted by high-skill hedge fund activists, but not by their low-skill peers. The difference in $\overline{ROA}_{mt}$ between targets of high-skill and low-skill activists amounts to 2.73% after four years from campaign initiation and further increases to 4.69% in the subsequent year. Both differences are significant at the 10% level. Overall, over the five years after the beginning of a campaign, targets of high-skill activists do see improvement in returns to assets, measured relative to a benchmark portfolio and compared to targets of low-skill activists peers. These differences emerge after about three years after campaign initiation. At the same time, targets of low-skill activists do not experience similar improvements in ROA post-activism.

Panel B of Figure 5 separately shows the average abnormal return on equity ($\overline{ROE}_{mt}$) for targets of our two groups of high- (left) and low-skill (right) activists. Similar to our findings for ROA, we observe a decline in $\overline{ROE}_{mt}$ for targets of high-skill activists in the pre-activism period. The decline continues for two years after campaign initiation when the abnormal return on equity turns around between years 2 and 3 of the activism campaign. In year 4, $\overline{ROE}_{mt}$ has entirely made up the decline we observed in the previous four years. By year 5, the average abnormal ROE exceeds its post-activism level by 6.98%, a difference that is significant at the 10% level. Target firms of low-skill activists experience a somewhat

[15] We provide detailed definitions of these measures in the appendix.

different performance pattern. Their average abnormal return on equity is slightly increasing in the pre-activism period. In the period after the announcement of the activist's campaign, their $\overline{ROE}_{mt}$ is relatively stable and insignificant. The most distinct difference between the two groups of target firms is the lack of improvment in performance in the later half of the post-activism period. A very similar picture emerges for our third measure of performance, average abnormal return on invested capital ($\overline{ROIC}_{mt}$). Considering target firms of high-skill activists in the left-hand portion of Panel C of Figure 5 reveals insignificant patterns in the pre-activism period and up to year 3 after campaign initiation. Years 4 and 5 again exhibit a sharp increase in performance, resulting in an average abnormal return on invested capital of 9.64% in year 4 and 12.23% in year 5. In contrast, targets of low-skill activists in the right-hand portion of Panel C show no distinctive changes in $\overline{ROIC}_{mt}$ over the entire 9-year sample period.

In summary, the above analysis suggests that when targets of skilled activists are not acquired, those targets experience significant improvements in operating performance over longer horizons post-activism. Such changes, however, do not materialize immediately but become most pronounced in the three to five years after campaign initiation. Targets of unskilled activists, on the other hand, do not experience similar performance improvements. Our analysis thus uncovers an important source of heterogeneity in the effect of activism on long-term operating performance along the dimension of activism skill.

5.4 Activist campaign specialization

Another characteristic of hedge fund activism campaigns is the set of tactics used during an active campaign. In our next set of tests, we explore whether high-skilled hedge fund activists are more specialized or more versatile in applying campaign tactics over the course of their engagements. Sun, Wang and Zheng (2012) investigate hedge fund performance and show that a more distinct investment strategy is associated with better subsequent fund performance. Following their idea, we analyze measures of distinctiveness in hedge fund activists' campaign tactics, and examine whether such measures vary across the distribution of hedge fund activism skill.

Factset provides a list of dissident tactics and reports indicators on tactics usage for each campaign. We report the full list of tactics and usage frequencies by hedge fund activism skill quintile in Appendix Table A2. Expanding the broad classification of tactics provided by Brav et al. (2008) in their Panel B of Table I, we summarize similar tactics into tactic clusters as shown in Column 2. Based on these clusters, for each hedge fund activist, we construct several measures of campaign specialization.

Our first two measures are simple counts of the average number of unique tactics used by hedge fund activists and the average number of total tactics used by hedge fund activists. We report averages for these measures by skill quintile in the left and middle portions of Figure 6. On average, a hedge fund activist employs 3.53 different tactics throughout its various campaigns. Focusing on the difference between hedge fund activists in the lowest- and in the highest-skill quintiles, we see that, on average, high-skill activists use slightly more than 3 different tactics across their campaigns, while low-skill activists use slightly less than 3 different tactics. The difference of 0.44 tactics is, however, not significant at conventional levels. Interestingly, we do find a spike in the average number of unique tactics used by the second highest-skill quintile, with almost 5 unique tactics used by the average hedge fund activist in this group. Moving to the average number of tactics used within a campaign, we find that hedge fund activists use an average of 1.68 tactics during each campaign. In contrast to our findings on the average number of unique tactics used, the number of total tactics used is monotonically increasing as we move from the low-skill to the high-skill hedge fund activist quintiles. The difference in average total tactics used between high-skill activists and their low-skill peers is 0.33 tactics, which is significant at the 10% level. Taken together, our first two measures suggest that high-skill hedge fund activists use a more diverse, and potentially more flexible, approach to engaging with their target firms. They employ a higher number of tactics during an average campaign, and they use a somewhat wider set of unique tactics across all of their campaigns.

Our last measure is designed to capture the degree of standardization vs. versatility in campaign tactics usage, and is similar to a standard deviation of campaign tactic scores. In particular, for each campaign, we first compute a tactic score that is based on the frequency of occurrences of the individual tactic clusters. We then compute the standard deviation of these tactic scores for each hedge fund activist, and require at least 2 campaigns per activist to be able to compute this measure. We provide a detailed example on how we construct this measures in Online Appendix C. By construction, our measure takes a value of 0 when activists use the same set of tactics in each of their campaigns, irrespective of the exact number of tactics that they use. The additional information we obtain from this measure over the previously introduced tactics counts thus lies in the variation or versatility of tactics usage. The measure increases in the degree to which an activist employs different sets of tactics across their campaigns. As such, low values of the measure represent activists that we would consider following a more standardized approach, while higher values of the measure represent more versatile activists. The right part of Figure 6 plots the average value of our specialization measure by hedge fund activist skill.

As is apparent from the figure, high-skilled activists are more flexible in their use of different dissident tactics. The specialization score slightly decreases as we move from the lowest-skill quintile to the 3rd quintile, then jumps up for the 2nd quintile, and remains high for the high-skill quintile. The difference in the average score between the high-skill quintile and the low-skill quintile is 0.65, which is again significant at the 10% level.[16] Taken together, our last measure confirms our previous assertion that high-skill activists do not seem to harvest benefits of specialization relative to their low-skill peers, but instead are more versatile in employing diverse strategies over the course of their campaigns.

5.5 Hostile resistance and counterresistance

Activism campaigns and activists' demands do not always remain unchallenged. Addressing the potential of hostile interactions between activists and targets, Boyson and Pichler (2019) examine how target firm resistance and hedge fund activists' counterresistance affect campaign outcomes and value implications. On average, when unopposed, target firm resistance results in negative market reactions and inferior campaign performances. When hedge funds counterresist, however, these effects do not persist. In this section, we expand our previous discussion on the usage of campaign tactics in the context of such target firm resistance. More specifically, we analyze whether hedge fund activism skill is related to the occurrence of target firm resistance, and conditional on facing such impediments, whether skill differences result in differences in hedge fund activists' counterresistence.

Following the methodology of Boyson and Pichler (2019), we first identify target resistance in our data and plot its occurrence by skill quintile in Panel A of Figure 7. On average, about 27.26% of the campaigns in our sample experience target firm resistance.

[16]This difference slightly increases to 0.70 when excluding the first category, *No Publicly Disclosed Activism*, from our analysis.

While resistance becomes less prevalent as we move from the lowest skill quintile to the third skill quintile, the percentage of campaigns that experience target firm resistance increases substantially for the second highest and the highest skill quintiles. As a result, hedge fund activists in the lowest and highest skill quintiles experience target resistance to a similar degree.

Hedge fund activists often respond to target firm resistance with counterresistance. We plot the percentage of campaigns that initiate counterresistance in Panel B of Figure 7. These campaigns are, by construction, a subset of the campaigns we have identified in Panel A. Overall, striking similarities between Panel A and Panel B emerge. While counterresistance declines as we move from the lowest to the medium skill quintile, it reverts to its initial level for the highest two skill quintiles. The resulting differences between the lowest and highest skill quintiles are again not statistically significant. A subtle difference does emerge however. While almost all campaigns initiated by low-skill hedge fund activists seem to show counterresistance, this does not seem to be the case for highly skilled activists. We confirm this pattern in Panel C of Figure 7. Here, we plot the percentage of campaigns in which hedge fund activists do not oppose target firm resistance, separately for each of our skill quintiles. Highly skilled hedge fund activists are significantly more likely than their less skilled peers to not respond to target firm resistance. The difference of 5.12% between the highest and lowest skill quintiles is significant at the 1% level.

In conclusion, while most cases of target firm resistance result in counterresistance on behalf of the hedge fund activist in our sample, highly skilled activists seem to be more selective when it comes to engaging in such confrontations. We believe that evidence for such behavior is consistent with our previous finding of a more versatile usage of campaign tactics in that the ability to avoid costly mistakes is an important dimension of skill in financial markets.

5.6 Supportive institutional shareholders

The literature has also recently emphasized the interplay between different institutional investors and their role in shareholder monitoring and activism (Hadlock and Schwartz-Ziv, 2019; Cvijanovic, Dasgupta and Zachariadis, 2019; Kedia, Starks and Wang, 2020). For example, Kedia et al. (2020) provide empirical evidence for a positive effect of pre-event, activism-friendly ownership on an activist's ability to create value in their campaign targets. In our context, these results raise the question of whether highly-skilled hedge fund activists are better able to utilize support from activism-friendly institutional investors than their lower-skilled peers. To examine this question, we follow Kedia et al. (2020) and construct the ownership share of supporting institutions ($OWNINC$) for each target firm in our sample. A supporting institution is defined as an investor who tends to increase its ownership in firms that are targeted by activists. We also contrast this ownership measure with the ownership share of all institutional investors and the ownership share of the hedge fund activist as reported at campaign initiation in the 13D filing.

We report averages for these three ownership measures for each of our hedge fund activism skill quintiles in Figure 8. With average activism-friendly ownership of 9.25%, average total institutional ownership of 57.66%, and average initial holdings by the activist of 9.46%, our sample produces similar statistics to those reported by Kedia et al. (2020). Interestingly, however, we find little heterogeneity across our skill quintiles. The difference in activism-friendly institutional ownership between the high-skill quintile and the low-skill quintile is actually negative at -0.15%, a difference that is not statistically significant. These results suggest that differences in activism outcomes that we attribute to skill are not driven by potential preferences for the presence of activism-friendly institutional investors.

We observe very similar results for the distribution of total institutional holdings. The most pronounced pattern in ownership is visible in the u-shaped pattern in initial activism holdings. Low- and high-skill activists are somewhat more likely to initiate their campaign with a higher equity stake in the target firm as compared to activists of other skill quintiles. For example, the difference between the average initial ownership percentage of 8.90% of the 3^{rd} skill quintile and the average initial ownership percentage of 10.92% of the highest- and lowest-skill quintile is highly statistically significant at the 1% level. The difference between the average initial ownership of the lowest and highest quintiles, however, is again not significant.

The literature has largely focused on the question of whether hedge fund activists are more likely to select targets with a high presence of activism-friendly institutional investors, and whether hedge fund activists can subsequently benefit from the presence of these institutional investors. In our analysis, we explore this question across the skill distribution of hedge fund activists. Our results indicate that higher ownership of activism-friendly institutional investors does not seem to play a major role in explaining heterogeneity in cumulative abnormal announcement returns across the hedge fund activism skill distribution.

6 Conclusion

Hedge fund activists have significantly shaped the realm of shareholder activism. Yet, due to a lack of data, our knowledge about the innate qualities of different hedge fund activists is somewhat limited. In this paper, we overcome some of these data challenges and estimate hedge fund activist-specific skills from cumulative abnormal announcement returns to 13D filings.

Applying a Markov Chain Monte Carlo Bayesian estimator to a data set that consists of $2,054$ campaigns that are initiated by 413 different hedge fund activists, we document significant dispersion in skill across those hedge fund activists. For example, our estimates imply that an inter-quartile change in the skill distribution of hedge fund activists results in a 14.60 percentage point increase in the average campaign's cumulative abnormal announcement return.[17]

The model also yields interesting results in out-of-sample tests. Our hedge fund-specific skill estimates are positively related to future cumulative abnormal announcement returns, suggesting that they indeed contain information about the long-term persistence in skill of those activists. We also examine risk-adjusted outperformance of investment strategies that use information about activists' skill and the timing of their campaign announcements. We find that investors can benefit from investing in targets of the high-skill hedge fund activists in our sample, but not from investing in targets of low-skill activists.

To contrast differences in stock picking ability from differences in value implications from activist involvement, we then examine whether hedge fund skill is associated with specific campaign characteristics and campaign outcomes. We find that target firms of high-skill hedge fund activists experience significant improvements in operating performance over a 5-year horizon after campaign announcement and measured relative to a benchmark portfolio of similar firms. At the same time, no improvement is visible in firms targeted by low-skill hedge fund activists. While high-skilled hedge fund activists in our sample are not more

[17]We obtain this point estimate when we measure cumulative abnormal announcement returns over a 12-day period from $t = -10$ to $t = +1$

likely to force their target firms into takeovers than their low-skill peers, we find significant differences in acquisition premiums between those groups. The average acquisition premium of proposed M&A deals for target firms of high-skill hedge fund activists is 27.42% percentage points higher than that of target firms of low-skill hedge fund activists. Moreover, we find that high-skilled hedge fund activists are more versatile in using strategies and tactics to achieve their campaign objectives. The average high-skill hedge fund activist utilizes a larger number of tactics per campaign and uses a larger number of unique tactics across all of its campaigns relative to lower-skill hedge fund activists. Finally, we also show that high-skill hedge fund activists are less likely to oppose target firm resistance than their low-skill peers. Avoiding costly mistakes may be a driver that contributes to the success for high-skill hedge fund activists in our sample.

Our results are consistent with skilled hedge fund activists taking an active role in the value enhancement of their target firms. They also point to important heterogeneity within the set of hedge fund activists that can be exploited by investors. Our empirical evidence highlights the importance of understanding campaign strategies and tactics when examining the determinants of value added by shareholder activism. To explore these elements for other groups of shareholder activists might be an interesting avenue to explore for future research.

References

Aiken, Adam L., Christopher P. Clifford, and Jesse Ellis (2013) "Out of the Dark: Hedge Fund Reporting Biases and Commercial Databases," *The Review of Financial Studies*, 26 (1), 208–243.

Albuquerque, Rui, Vyacheslav Fos, and Enrique Schroth (2021) "Value creation in shareholder activism," *Journal of Financial Economics*.

Aragon, George O. and Vikram Nanda (2017) "Strategic Delays and Clustering in Hedge Fund Reported Returns," *Journal of Financial and Quantitative Analysis*, 52 (1), 1–35.

Avramov, Doron, Robert Kosowski, Narayan Y. Naik, and Melvyn Teo (2011) "Hedge funds, managerial skill, and macroeconomic variables," *Journal of Financial Economics*, 99 (3), 672–692.

Avramov, Doron and Russ Wermers (2006) "Investing in mutual funds when returns are predictable," *Journal of Financial Economics*, 81 (2), 339–377.

Baks, Klaas P., Andrew Metrick, and Jessica Wachter (2001) "Should Investors Avoid All Actively Managed Mutual Funds? A Study in Bayesian Performance Evaluation," *The Journal of Finance*, 56 (1), 45–85.

Baquero, Guillermo, Jenke ter Horst, and Marno Verbeek (2005) "Survival, look-ahead bias, and persistence in hedge fund performance," *Journal of Financial and Quantitative Analysis*, 493–517.

Barber, Brad M and John D Lyon (1997) "Detecting long-run abnormal stock returns: The empirical power and specification of test statistics," *Journal of financial economics*, 43 (3), 341–372.

Bebchuk, Lucian A., Alon Brav, and Wei Jiang (2015) "The Long-Term Effects of Hedge Fund Activism," *Columbia Law Review*, 115 (5), 1085–1155.

Becht, Marco, Julian Franks, Jeremy Grant, and Hannes F. Wagner (2017) "Returns to Hedge Fund Activism: An International Study," *The Review of Financial Studies*, 30 (9), 2933–2971.

Becht, Marco, Julian Franks, Colin Mayer, and Stefano Rossi (2009) "Returns to shareholder activism: Evidence from a clinical study of the Hermes UK Focus Fund," *The Review of Financial Studies*, 22 (8), 3093–3129.

Boyson, Nicole M., Nickolay Gantchev, and Anil Shivdasani (2017) "Activism mergers," *Journal of Financial Economics*, 126 (1), 54–73.

Boyson, Nicole M, Linlin Ma, and Robert M Mooradian (2022) "How does past experience impact hedge fund activism?" *Journal of Financial and Quantitative Analysis*, 57 (4), 1279–1312.

Boyson, Nicole M and Pegaret Pichler (2019) "Hostile resistance to hedge fund activism," *The Review of Financial Studies*, 32 (2), 771–817.

Brav, Alon, Wei Jiang, Hyunseob Kim et al. (2010) "Hedge fund activism: A review," *Foundations and Trends® in Finance*, 4 (3), 185–246.

Brav, Alon, Wei Jiang, and Hyunseob Kim (2015) "Recent advances in research on hedge fund activism: Value creation and identification," *Annual Review of Financial Economics*, 7, 579–595.

Brav, Alon, Wei Jiang, Frank Partnoy, and Randall Thomas (2008) "Hedge fund activism, corporate governance, and firm performance," *The Journal of Finance*, 63 (4), 1729–1775.

Busse, Jeffrey A. and Paul J. Irvine (2006) "Bayesian Alphas and Mutual Fund Persistence," *The Journal of Finance*, 61 (5), 2251–2288.

Clifford, Christopher P (2008) "Value creation or destruction? Hedge funds as shareholder activists," *Journal of Corporate Finance*, 14 (4), 323–336.

Cremers, Martijn, Erasmo Giambona, Simone M Sepe, and Ye Wang (2021) "Hedge Fund Activists: Value Creators or Good Stock Pickers?" *Erasmo and Sepe, Simone M. and Wang, Ye, Hedge Fund Activists: Value Creators or Good Stock Pickers*.

Cvijanovic, Dragana, Amil Dasgupta, and Konstantinos E. Zachariadis (2019) "The Wall Street Stampede: Exit as Governance with Interacting Blockholders," *CEPR Discussion Paper No. DP13870*.

DeHaan, Ed, David Larcker, and Charles McClure (2019) "Long-term economic consequences of hedge fund activist interventions," *Review of Accounting Studies*, 24 (2), 536–569.

Edwards, Franklin R. and Mustafa Onur Caglayan (2001) "Hedge Fund Performance and Manager Skill," *Journal of Futures Markets*, 21 (11), 1003–1028.

Fung, William, David A. Hsieh, Narayan Y. Naik, and Tarun Ramadorai (2008) "Hedge funds: Performance, risk, and capital formation," *The Journal of Finance*, 63 (4), 1777–1803.

Gelfand, Alan E and Adrian FM Smith (1990) "Sampling-based approaches to calculating marginal densities," *Journal of the American Statistical Association*, 85 (410), 398–409.

Geman, Stuart and Donald Geman (1984) "Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images," *IEEE Transactions on Pattern Analysis and Machine Intelligence* (6), 721–741.

Greenwood, Robin and Michael Schor (2009) "Investor activism and takeovers," *Journal of Financial Economics*, 92 (3), 362–375.

Hadlock, Charles J and Miriam Schwartz-Ziv (2019) "Blockholder Heterogeneity, Multiple Blocks, and the Dance between Blockholders," *The Review of Financial Studies*, 32 (11), 4196–4227.

Harvey, Campbell R and Yan Liu (2018) "Detecting Repeatable Performance," *The Review of Financial Studies*, 31 (7), 2499–2552.

Jagannathan, Ravi, Alexey Malakhov, and Dmitry Novikov (2010) "Do hot hands exist among hedge fund managers? An empirical evaluation," *The Journal of Finance*, 65 (1), 217–255.

Jiang, Wei, Tao Li, and Danqing Mei (2018) "Influencing control: Jawboning in risk arbitrage," *The Journal of Finance*, 73 (6), 2635–2675.

Johnson, Norman J (1978) "Modified t tests and confidence intervals for asymmetrical populations," *Journal of the American Statistical Association*, 73 (363), 536–544.

Johnson, Travis L. and Nathan Swem (2021) "Reputation and investor activism: A structural approach," *Journal of Financial Economics*, 139 (1), 29–56.

Jones, Christopher S. and Jay Shanken (2005) "Mutual fund performance with learning across funds," *Journal of Financial Economics*, 78 (3), 507–552.

Kedia, Simi, Laura T. Starks, and Xianjue Wang (2020) "Institutional Investors and Hedge Fund Activism," *The Review of Corporate Finance Studies*, 10 (1), 1–43.

Klein, April and Emanuel Zur (2009) "Entrepreneurial shareholder activism: Hedge funds and other private investors," *The Journal of Finance*, 64 (1), 187–229.

Korteweg, Arthur G (2013) "Markov chain Monte Carlo methods in corporate finance," in Damien, Paul, Petros Dellaportas, Nicholas G. Polson, and David A. Stephens eds. *Bayesian Theory and Applications*, Chap. 26, 516–545: Oxford University Press.

Korteweg, Arthur and Morten Sorensen (2017) "Skill and Luck in Private Equity Performance," *Journal of Financial Economics*, 124 (3), 535–562.

Kosowski, Robert, Narayan Y. Naik, and Melvyn Teo (2007) "Do hedge funds deliver alpha? A Bayesian and bootstrap analysis," *Journal of Financial Economics*, 84 (1), 229–264.

Kothari, SP and Jerold B Warner (1997) "Measuring long-horizon security price performance," *Journal of financial economics*, 43 (3), 301–339.

Krishnan, CNV, Frank Partnoy, and Randall S Thomas (2016) "The second wave of hedge fund activism: The importance of reputation, clout, and expertise," *Journal of Corporate Finance*, 40, 296–314.

Lyon, John D, Brad M Barber, and Chih-Ling Tsai (1999) "Improved methods for tests of long-run abnormal stock returns," *The Journal of Finance*, 54 (1), 165–201.

Pástor, Luboš and Robert F. Stambaugh (2002) "Investing in equity mutual funds," *Journal of Financial Economics*, 63 (3), 351–380.

Rossi, Peter E, Greg M Allenby, and Rob McCulloch (2012) *Bayesian Statistics and Marketing*: John Wiley & Sons.

Sun, Zheng, Ashley Wang, and Lu Zheng (2012) "The Road Less Traveled: Strategy Distinctiveness and Hedge Fund Performance," *The Review of Financial Studies*, 25 (1), 96–143.

Wu, Szu-Yin (Jennifer) and Kee H. Chung (2021) "Hedge Fund Activism and Corporate MA Decisions," *Management Science (forthcoming)*.

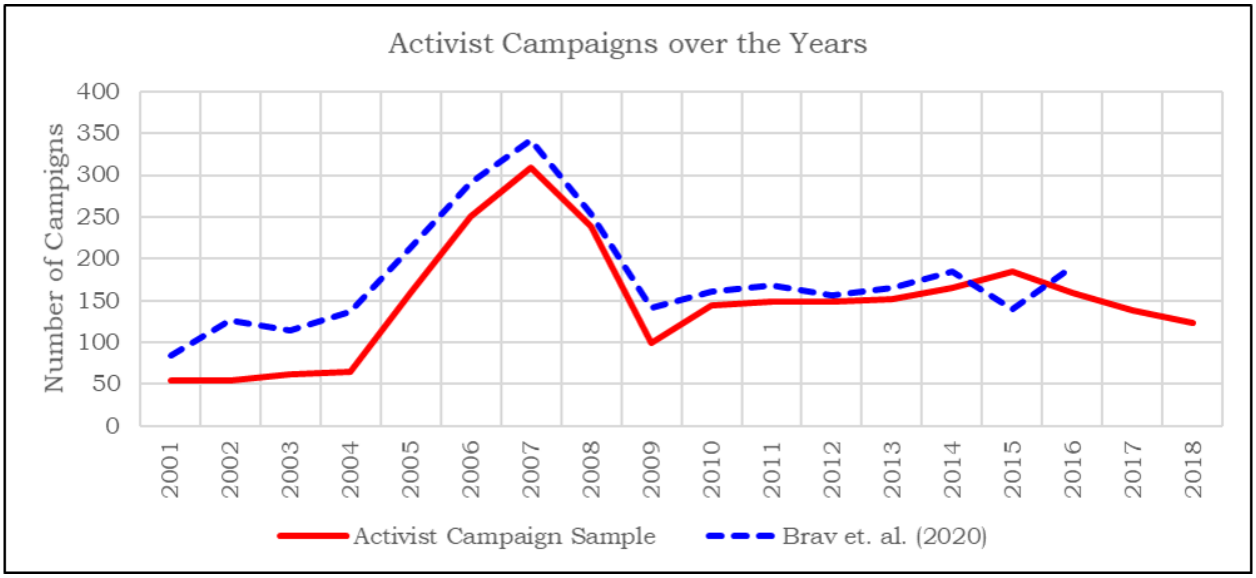

Figure 1: **Number of Hedge Fund Activist Campaigns per Year**
This figure compares the annual number of hedge fund activist campaigns between our sample and a sample that uses the same data collection procedure and estimation methods as in Brav et al. (2008) and Brav et al. (2010). This updated sample is provided on Alon Brav's website. The solid line represents our sample, which is based on Shark Repellent's hedge fund activism data from 2001 - 2018. Each campaign in our sample is initiated by a Schedule 13D filing. The dashed line represents the updated sample of Brav et al. (2008) and Brav et al. (2010), which is available from 2001 to 2016.

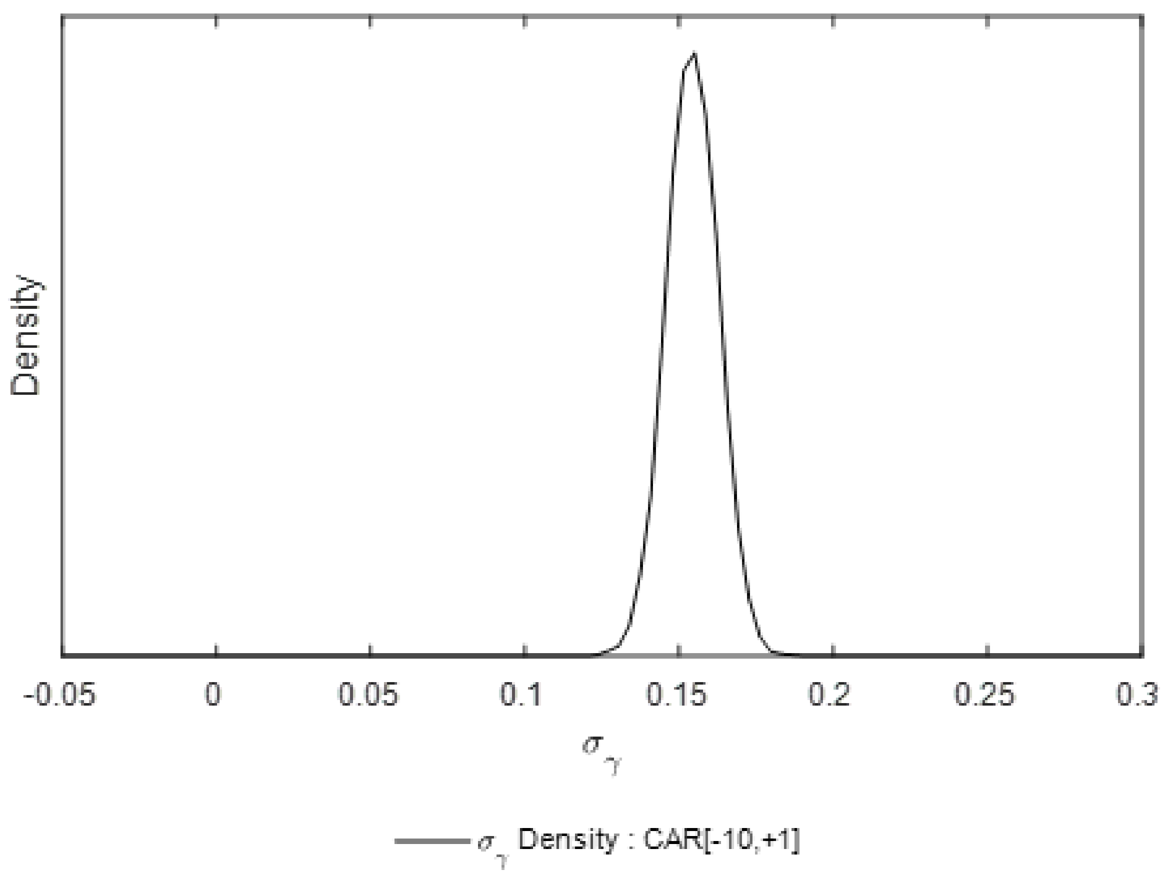

Figure 2: **Posterior Distribution of σ_γ : $y_{ic} = CAR[-10, +1]$ using the Fama-French 3-Factor model for Expected Returns**
This figure plots the posterior distribution of standard deviation (σ_γ) of the hedge fund-specific random effect (γ_i); estimated with the dependent variable (in the model Eq. (1)) y_{ic} as the CAR for event window $[-10, +1]$ (calculated using the Fama-French 3-Factor model). The mean of the posterior distribution of σ_γ is 0.154, with Bayesian standard error 0.006 and p-value nearly zero, strongly rejecting the null hypothesis $H_0 : \sigma_\gamma = 0$.

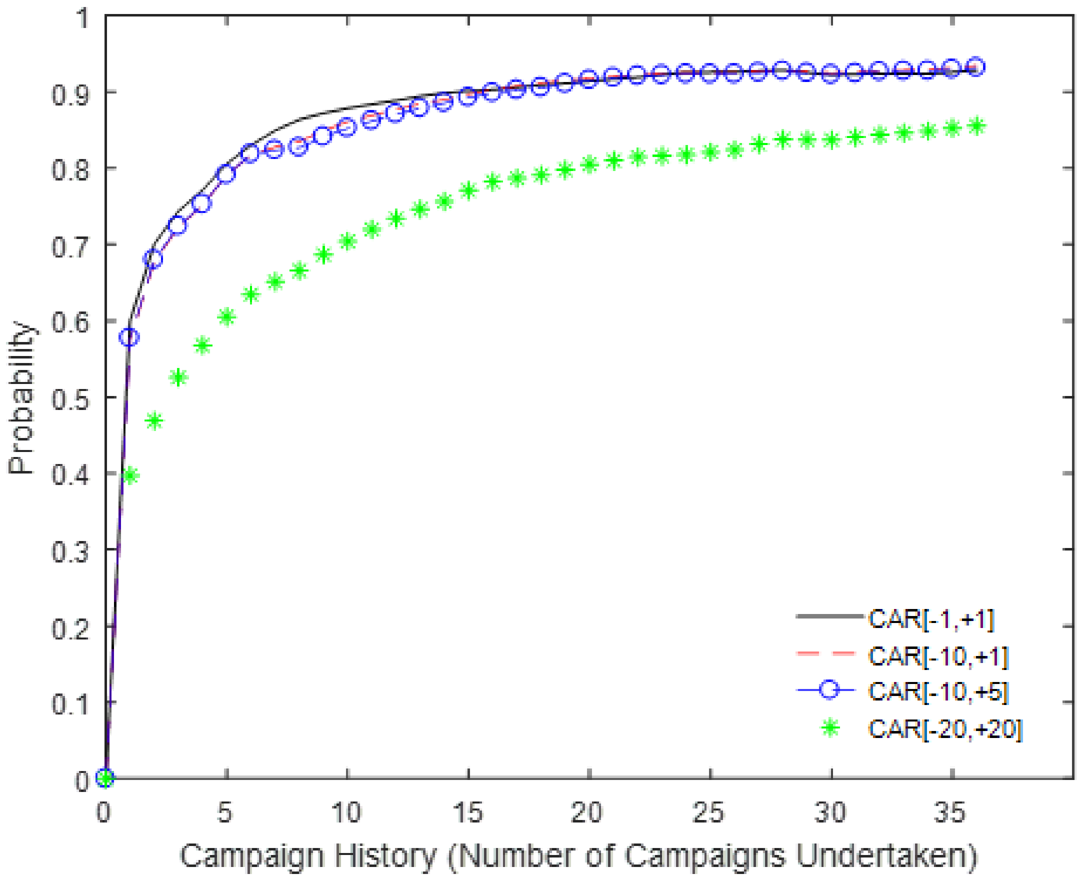

Figure 3: **Speed of Learning : $y_{ic} = CAR$ for Different Event Windows using Fama-French Three Factor Model for Expected Returns**
This figure plots the speed of learning estimated with the dependent variable (in the model Eq. (1)) y_{ic} as the CAR calculated using the Fama-French 3-Factor model; for event windows $[-1, +1]$ (solid black line), $[-10, +1]$ (dashed red line), $[-10, +5]$ (bubbled blue line) and $[-20, +20]$ (starred green line). The speed of learning estimates using any of the metrics: $CAR[-1, +1]$, $CAR[-10, +1]$ and $CAR[-10, +5]$ are almost identical. It takes about five campaigns, to identify hedge fund activists that can be expected to have top quintile CAR in future campaigns; with about 79% certainty. An interesting thing to note is: Since the signal-to-noise ratio (S_γ) is small for CARs over the $[-20, +20]$ event window; the speed of learning about hedge fund activist skill is much slower using $CAR[-20, +20]$ as a metric of value added to target firms by hedge fund activists. It takes about 20 campaigns worth of observed history to identify skilled activist hedge funds; with same certainty (79%); using $CAR[-20, +20]$ as the metric for value added by hedge fund activists at target firms.

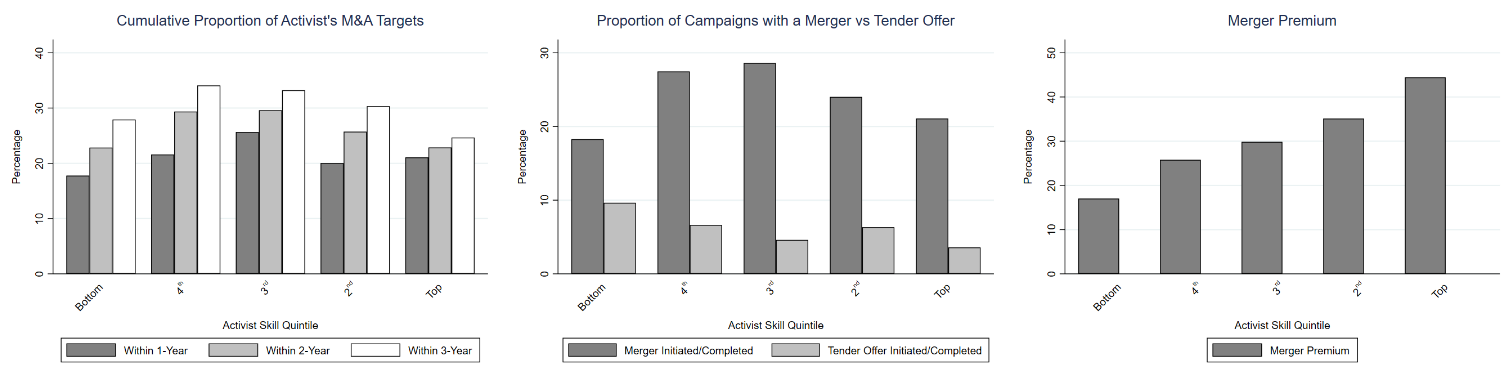

Figure 4: **Activism campaigns and M&A activity**

This figure documents the propensity of being taken over as a target firm of hedge fund activism as well as average proposed acquisition premiums. We separately report averages of all measures by hedge fund activist skill quintile. On the left, we show the fraction of targets that are taken over within 1, 2, and 3 years after the initial 13D filing of the hedge fund activist, respectively. In the middle, we separate takeover mechanisms into mergers and tender offers, and report the average fraction of targets that are taken over within 3 years of a campaign's initiation. On the right, we report the average acquisition premium, computed following Boyson et al. (2017) on a per-share basis as the offer price relative to the target's stock price 25 days prior to merger announcement. Our sample covers the period from 2001 to 2018.

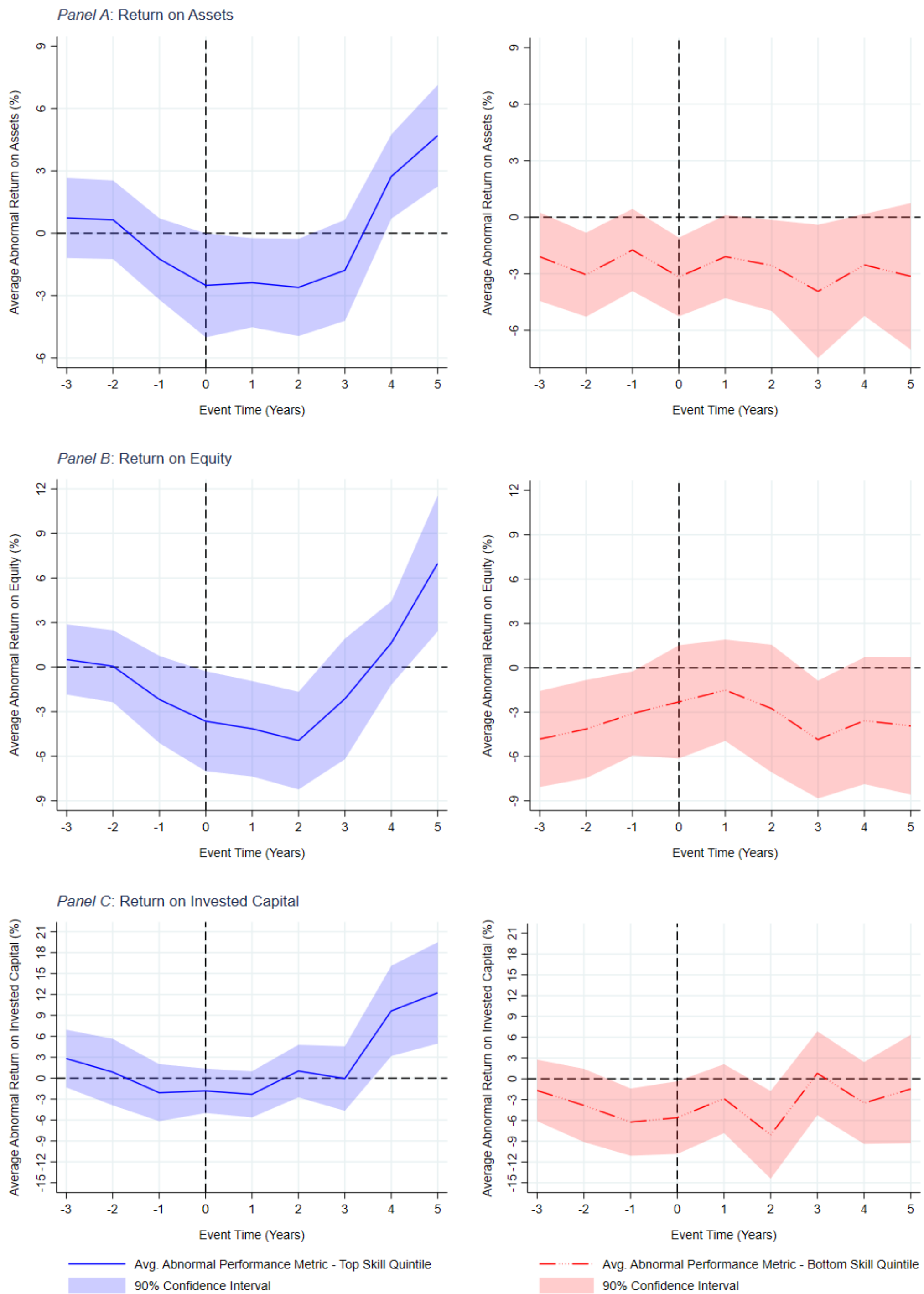

Figure 5: **Target Firm Performance Post-Activism**

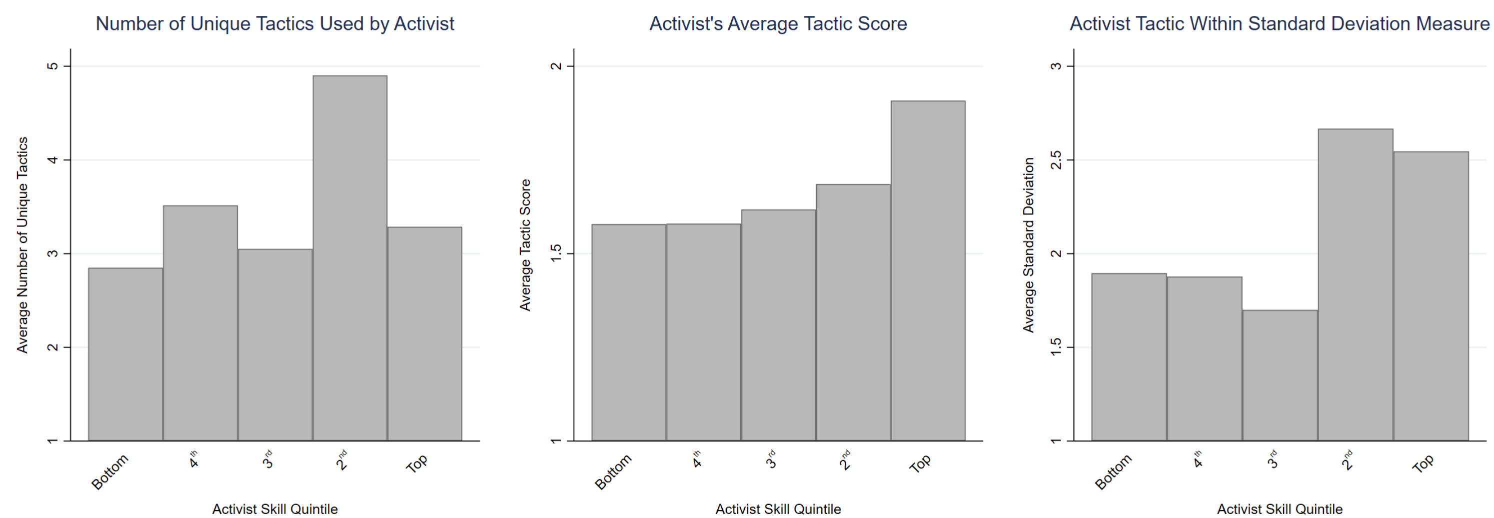

Figure 6: **Campaign specialization and tactics used**
This figure documents the degree of specialization in campaign tactics used by hedge fund activists. We separately report averages of all measures by hedge fund activist skill quintile. On the left, we count the number of unique tactics used by hedge fund activists across all of a fund's activism campaigns. In the middle, we compute the average number of tactics used by hedge fund activists in a single campaign. On the right, we compute a measure that can be thought of as a standard deviation of campaign tactic scores. Higher values of this measure indicate more variety in the set of tactics employed by hedge fund activists across their campaigns. The construction of this measure is explained in Online Appendix C. Our sample covers the period from 2001 to 2018.

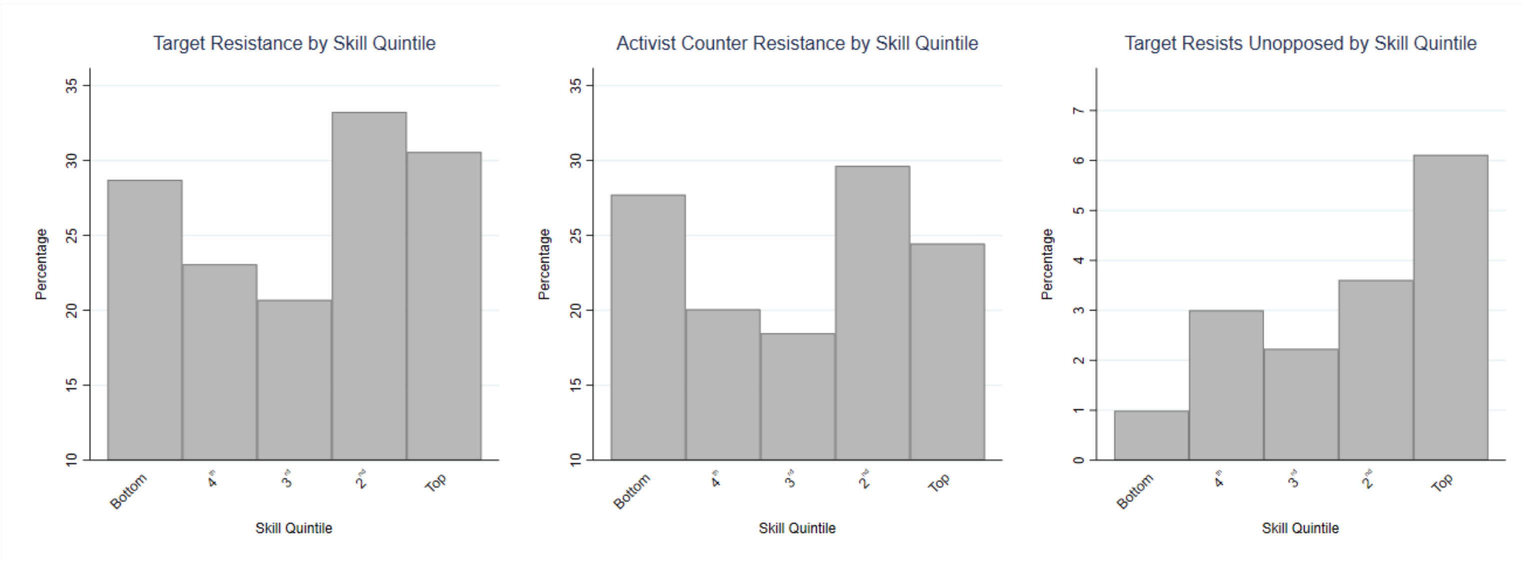

Figure 7: **Hostile Resistance and Counterresistance**
This figure documents the propensity of target firms to resist intervention by hedge fund activists and the activist's counter response to target firms' resistance. The resistance and counterresistance measures are constructed as defined in Boyson and Pichler (2019). The left panel depicts the fraction of campaigns where the target firm formally resists the activist's engagement. In the middle, we show the fraction of campaigns where the hedge fund activist counterresists the initial resistance of the target firm. On the right, we display the fraction of campaigns where the hedge fund activist chooses to not launch a counterresistance to the resistance offered by the target firm. Our sample covers the period from 2001 to 2018.

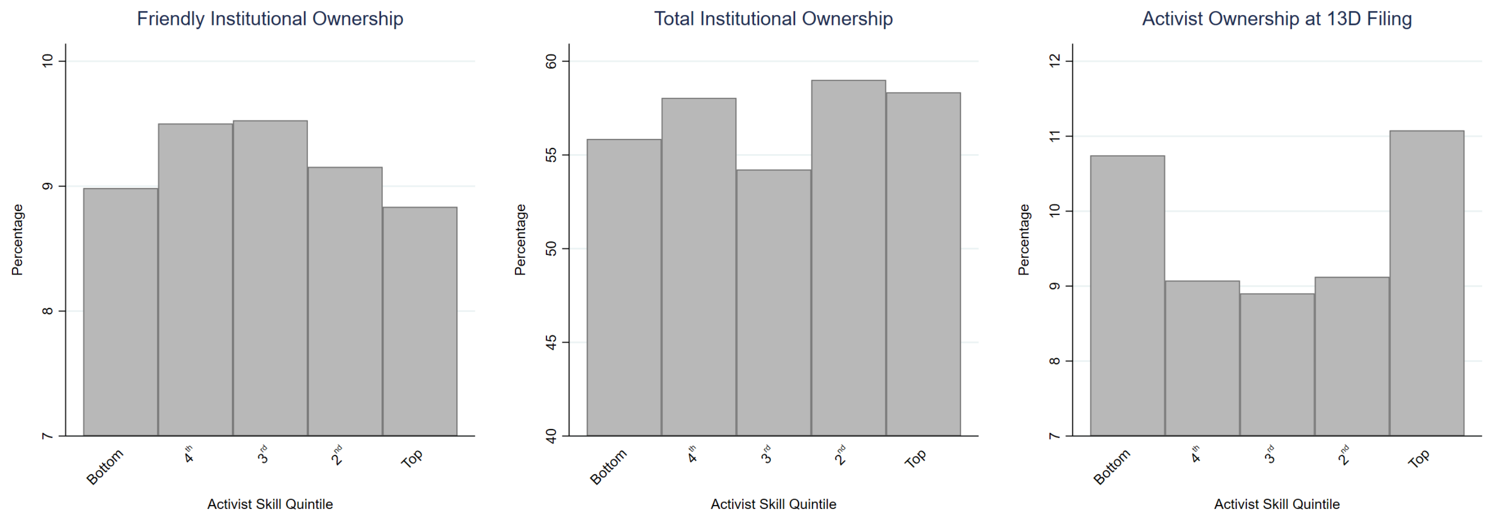

Figure 8: **Supportive Ownership**
This figure documents institutional ownership patterns in target firms around the filing of a 13D by a hedge fund activist. We separately report all ownership percentages by hedge fund activist skill quintile. On the left, we show pre-event activism-friendly ownership percentages, defined by Kedia et al. (2020) as the fraction of institutional investors who tend to increase their ownership in firms that are targeted by activists. In the middle, we show ownership percentages by all institutional investors, irrespective of their type. On the right, we display ownership percentages of those hedge fund activists that initiate a campaign, as reported in the associated 13D filing. Our sample covers the period from 2001 to 2018.

Table 1: **Announcement Returns to Hedge Fund Activism**

This table reports the (observed) distribution characteristics of the cumulative abnormal return (CAR) for our sample of $2,054$ activist campaigns in Panel A. In Panel B we report the average cumulative abnormal return ($CAAR$) across all campaigns undertaken by each of the 413 hedge fund activists in the sample. Both CARs and $CAAR$s are reported for different event windows ($[-1,+1]$, $[-10,+1]$, $[-10,+5]$, and $[-20,+20]$) and are calculated using the "Fama/French Three Factor" expected return model. Column 2 gives the number of observations (N). Columns 3 and 4 report the mean and standard deviation; Columns 5 through 11 give the 1^{st}, 10^{th}, 25^{th}, Median, 75^{th}, 90^{th} and 99^{th} percentiles for the distribution of each reported metric.

Variable (1)	N (2)	Mean (3)	Std. (4)	1% (5)	10% (6)	25% (7)	50% (8)	75% (9)	90% (10)	99% (11)
Panel A: Cumulative Abnormal Return [CAR]										
$CAR[-1,+1]$	2054	3.54%	15.19%	-14.88%	-3.35%	-0.60%	2.08%	6.10%	11.46%	34.38%
$CAR[-10,+1]$	2054	4.92%	20.22%	-36.54%	-10.14%	-2.17%	3.99%	11.37%	20.51%	49.45%
$CAR[-10,+5]$	2054	5.73%	21.15%	-35.92%	-11.25%	-2.56%	4.56%	12.85%	23.34%	53.43%
$CAR[-20,+20]$	2054	7.09%	27.66%	-62.60%	-18.91%	-4.93%	6.22%	18.63%	32.62%	82.83%
Panel B: Cumulative Average Abnormal Return [CAAR]										
$CAAR[-1,+1]$	413	3.98%	15.83%	-16.77%	-2.63%	0.21%	2.36%	5.89%	10.72%	33.07%
$CAAR[-10,+1]$	413	4.55%	21.16%	-49.66%	-9.29%	-1.42%	3.87%	9.36%	17.85%	40.10%
$CAAR[-10,+5]$	413	5.72%	21.99%	-34.79%	-9.72%	-1.65%	4.45%	11.34%	21.81%	57.80%
$CAAR[-20,+20]$	413	7.40%	25.49%	-52.12%	-17.30%	-0.72%	7.10%	15.60%	26.83%	66.77%

Table 2: **Parameter Estimates**

This table reports posterior means of parameters of the model described in the text, using CAR based on "Fama-French Three Factor Model" as the dependent variable. Panel A shows the parameter estimates, and Panel B shows the spread in gammas across percentiles of the posterior distribution, where; $q_\gamma(75\%)-q_\gamma(25\%)$ is the spread in expected value added (at a target firm) by the marginal top and bottom quartile hedge fund activist, $q_\gamma(80\%)-q_\gamma(20\%)$ is the spread in expected value added (at a target firm) by the marginal top and bottom quintile hedge fund activist, and $q_\gamma(90\%)-q_\gamma(10\%)$ is the spread in expected value added (at a target firm) by the marginal top and bottom decile hedge fund activist. The model is estimated separately for CARs over different event windows ($[-1,+1],[-10,+1],[-10,+5],[-20,+20]$) around the filing of a 13D by a hedge fund activist, by Markov chain Monte Carlo (MCMC) using $10,000$ burn-in cycles followed by $100,000$ samples, saving every 10^{th} draw. Each specification controls for year fixed effects. Posterior standard deviations (Bayesian standard errors) are given in brackets.

	(1)	(2)	(3)	(4)
Cumulative Abnormal Return Specification				
Expected Return Model	Fama-French Three Factor Model			
Event Window	[-1,+1]	[-10,+1]	[-10,+5]	[-20,+20]
Panel A: Parameter Estimates				
σ_γ	0.126	0.154	0.162	0.095
	(0.006)	(0.008)	(0.008)	(0.017)
σ_ϵ	0.128	0.174	0.181	0.265
	(0.002)	(0.002)	(0.003)	(0.004)
Year-Fixed Effects	Yes	Yes	Yes	Yes
N	2054	2054	2054	2054
Bayes Factor	>100	>100	>100	>100
p-Value	0.000	0.000	0.000	0.000
Panel B: Gamma Spread				
$q_\gamma(75\%)-q_\gamma(25\%)$	10.30%	14.60%	15.70%	11.90%
	(0.006)	(0.009)	(0.010)	(0.019)
$q_\gamma(80\%)-q_\gamma(20\%)$	13.10%	18.60%	20.00%	14.90%
	(0.007)	(0.011)	(0.012)	(0.024)
$q_\gamma(90\%)-q_\gamma(10\%)$	21.20%	30.00%	32.10%	22.90%
	(0.011)	(0.016)	(0.017)	(0.037)

Table 3: **Out of Sample Tests: The Relation between Performance and Skill (γ)**
In this table, we report results of a test that examines the out of sample validity of our activist skill estimates (γ). To perform this test, we split the sample period (2001 – 2018) into two phases: *Learning Phase* (2001 – 2012) and *Testing Phase* (2013 – 2018). First, we estimate hedge fund specific skill effects (γ) with our Bayesian estimation technique over the *Learning Phase*. We only use activists if they have at least one campaign in the *Learning Phase* as well as the *Testing Phase*. Then, in specification 1, we regress 11-day cumulative abnormal returns ($CAR[-10, +1]$ based on the Fama-French Three Factor Model) on our estimated skill coefficients γ over the *Testing Phase*. In specification 2 we control for the activist's frequency of undertaking campaigns (annually). Specification 3 controls for target firm characteristics a year prior to the year in which the campaign is undertaken against the target. The control variables used are the target's Market Capitalization, Tobin's Q Ratio, Sales (scaled by lagged total assets), Return on Assets (ROA), Cash Flow (scaled by lagged total assets), Leverage, Cash balance (scaled by lagged total assets), Dividend Yield, and R&D (scaled by lagged total assets). Variable definitions are provided in the appendix. Finally, specification 4 includes our full set of control variables. All specifications include year fixed effects.

Learning Phase	2001 – 2012			
Variable	(1)	(2)	(3)	(4)
Estimated γ	0.863*	0.952*	0.661**	0.634**
	(2.528)	(2.499)	(2.382)	(2.169)
Annual Campaign Frequency		-0.012		0.003
		(-1.468)		(0.595)
Market Capitalization			-0.000	-0.000
			(-0.729)	(-0.892)
Tobin's Q Ratio			0.003	0.003
			(0.453)	(0.450)
Sales			-0.002	-0.002
			(-0.114)	(-0.103)
ROA			-0.271	-0.283
			(-0.888)	(-0.918)
Cash Flow			0.232	0.244
			(0.832)	(0.865)
Leverage			-0.032	-0.032
			(-0.982)	(-0.971)
Cash			-0.030	-0.028
			(-1.074)	(-0.962)
Dividend Yield			0.179	0.187
			(0.687)	(0.722)
R&D			-0.076	-0.079
			(-0.559)	(-0.590)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	458	458	334	334
R-squared	0.015	0.018	0.043	0.044

Table 4: **Calendar-Time Portfolio Regressions**

This table reports regression estimates and t-statistics from equal-weighted calendar-time portfolio regressions. "Model" indicates the factor model used to estimate monthly risk-adjusted "Alpha," where "Alpha" is the estimate of the regression intercept from the factor models. Regression results from using three factor models are presented here: "Fama-French 3-Factor," "Fama-French 3-Factor plus Carhart Momentum Factor," and the "Fama-French 5-Factor" models. "Beta" is the factor loading on the market excess return (the Fama and French RMRF). "SMB," "HML," and "MOM" are the estimates of factor loading on the Fama-French size and book-to-market factors, and the Carhart momentum factor. For the "Fama-French 5-Factor" model "SMB," "HML," "RMW," and "CMA" are the estimates of factor loading on the Fama-French size, book-to-market, profitability, and investment factors as defined for "Fama-French 5-Factor" model. "Hold for" indicates the holding period for securities in our calendar-time portfolio. Panel A reports the regression results for a long-only mimicking strategy, assuming that an investor purchases shares in the same target firm as the top quintile of hedge fund activists. The ranking of activists into quintiles here is based on their estimated skill (γ). This ranking is constructed every year $t-1$, based on which in year t we take long positions in the targets of the top quintile of hedge fund activists for 3-, 6-, 9-, and 12-month holding periods. The resulting equal-weighted portfolio of securities is re-balanced each month depending on availability of new targets and expiration of holding periods of older targets in the portfolio. Panel B reports regression results for a simpler long-only mimicking strategy, where the activists are ranked into quintiles based on the average observed CARs for each activist till year $t-1$. Panel C reports the regression results for a long-only mimicking strategy, assuming that an investor purchases shares in the same target firm as the bottom quintile of hedge fund activists. The ranking of activists into quintiles here is based on their estimated skill (γ). ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Model	Fama-French 3-Factor				Fama-French 5-Factor			
Hold for	3-Mth	6-Mth	9-Mth	12-Mth	3-Mth	6-Mth	9-Mth	12-Mth
Panel A: Top Quintile Activists [Ranked Based on Estimated γ]								
Alpha	0.015**	0.014**	0.008*	0.008**	0.015**	0.015**	0.009*	0.010***
	(2.523)	(2.426)	(1.765)	(2.320)	(2.493)	(2.533)	(1.964)	(2.811)
Beta	0.700***	0.640***	0.697***	0.700***	0.668***	0.582***	0.636***	0.604***
	(4.395)	(4.041)	(5.532)	(6.966)	(3.835)	(3.359)	(4.651)	(5.623)
SMB	0.975***	0.874***	0.850***	0.652***	0.938***	0.760***	0.704***	0.466***
	(3.641)	(3.292)	(4.193)	(4.050)	(3.301)	(2.708)	(3.332)	(2.817)
HML	0.123	0.419*	0.345*	0.135	-0.055	0.336	0.192	0.005
	(0.487)	(1.744)	(1.874)	(0.921)	(-0.191)	(1.211)	(0.906)	(0.028)
RMW					-0.168	-0.341	-0.404	-0.595***
					(-0.445)	(-0.937)	(-1.482)	(-2.781)
CMA					0.179	-0.098	0.172	0.187
					(0.393)	(-0.217)	(0.495)	(0.692)

Continued on next page –

– continued from previous page

Model	Fama-French 3-Factor				Fama-French 5-Factor			
Hold for	3-Mth	6-Mth	9-Mth	12-Mth	3-Mth	6-Mth	9-Mth	12-Mth
Panel B: Top Quintile Activists [Ranked Based on Average CAAR]								
Alpha	0.014	0.009	0.008	0.006	0.016	0.008	0.009	0.006
	(1.417)	(1.099)	(1.218)	(0.996)	(1.490)	(1.032)	(1.370)	(1.078)
Beta	0.691**	0.798***	0.804***	0.953***	0.645**	0.818***	0.746***	0.923***
	(2.573)	(3.749)	(4.521)	(6.007)	(2.148)	(3.507)	(3.850)	(5.345)
SMB	0.677	0.720**	0.792***	0.511**	0.419	0.571	0.608**	0.380
	(1.499)	(2.035)	(2.754)	(1.979)	(0.882)	(1.540)	(2.030)	(1.416)
HML	0.136	0.094	0.234	0.524**	-0.040	-0.150	0.055	0.333
	(0.320)	(0.290)	(0.868)	(2.041)	(-0.081)	(-0.391)	(0.178)	(1.142)
RMW					-0.496	-0.098	-0.466	-0.311
					(-0.783)	(-0.201)	(-1.208)	(-0.893)
CMA					0.501	0.524	0.312	0.433
					(0.624)	(0.829)	(0.642)	(0.983)
Panel C: Bottom Quintile Activists [Ranked Based on Estimated γ]								
Alpha	0.005	0.005	0.003	0.002	0.006	0.005	0.003	0.002
	(0.717)	(1.217)	(0.867)	(0.522)	(0.850)	(1.062)	(0.903)	(0.445)
Beta	0.790***	0.712***	0.727***	0.706***	0.708***	0.722***	0.717***	0.711***
	(4.805)	(5.809)	(7.708)	(7.684)	(3.862)	(5.335)	(6.896)	(6.969)
SMB	1.365***	0.914***	0.930***	0.958***	1.272***	0.932***	0.930***	0.965***
	(4.736)	(4.546)	(5.908)	(6.332)	(4.283)	(4.481)	(5.686)	(6.067)
HML	-0.275	-0.400**	-0.144	0.008	-0.553*	-0.589***	-0.174	-0.090
	(-1.021)	(-2.158)	(-0.995)	(0.057)	(-1.856)	(-2.792)	(-1.060)	(-0.566)
RMW					-0.411	0.078	-0.044	0.022
					(-1.044)	(0.280)	(-0.203)	(0.103)
CMA					0.359	0.183	-0.402	-0.170
					(0.733)	(0.530)	(-1.477)	(-0.649)

End of Table 4

Table 5: **Variance Decomposition for Model Parameters**
This table reports the variance decomposition estimates for the model parameters, along with the Signal-to-Noise ratio ($=\sigma_\gamma^2/\sigma_y^2$) estimates. The model is estimated separately for CARs over different event windows ($[-1,+1],[-10,+1],[-10,+5],[-20,+20]$) around the filing of a 13D by a hedge fund activist, by Markov chain Monte Carlo (MCMC) using $10,000$ burn-in cycles followed by $100,000$ samples, saving every 10^{th} draw. Each specification controls for year fixed effects. Posterior standard deviations (Bayesian standard errors) are given in brackets.

	I	II	III	IV
Cumulative Abnormal Return Specification				
Expected Return Model	Fama-French Three Factor Model			
Event Window	[-1,+1]	[-10,+1]	[-10,+5]	[-20,+20]
σ_γ^2	0.016	0.024	0.026	0.009
	(0.001)	(0.003)	(0.003)	(0.003)
σ_ϵ^2	0.016	0.030	0.033	0.070
	(0.000)	(0.001)	(0.001)	(0.002)
σ_y^2	0.032	0.054	0.059	0.079
	(0.001)	(0.002)	(0.003)	(0.003)
Signal-to-Noise	0.491	0.440	0.444	0.116
	(0.026)	(0.029)	(0.028)	(0.037)

Appendix

Variable Definitions

σ_γ^2 is the posterior estimate of the variance of the distribution of time-invariant hedge fund-specific component of cumulative abnormal announcement returns around the filing of a Schedule 13D by a hedge fund activist. The standard deviation (σ_γ) is just the square root of this variance.

σ_ϵ^2 is the posterior estimate of the idiosyncratic error component of cumulative abnormal announcement returns around the filing of a Schedule 13D by a hedge fund activist. The standard deviation (σ_ϵ) is just the square root of this error.

σ_y^2 is the total variance of the cumulative abnormal announcement returns around the filing of a Schedule 13D by a hedge fund activist.

Signal-to-Noise ratio (S_γ) is calculated as $\sigma_\gamma^2/\sigma_y^2$. Thus it is the proportion of total variance in cumulative abnormal announcement returns contributed by the variance in the hedge fund-specific component. Hence a higher S_γ implies a stronger signal of hedge fund activist's skill in the announcement returns.

$q_\gamma(75\%)-q_\gamma(25\%)$ is the spread in expected value added (at a target firm) by the marginal top and bottom quartile hedge fund activist.

$q_\gamma(80\%)-q_\gamma(20\%)$ is the spread in expected value added (at a target firm) by the marginal top and bottom quintile hedge fund activist.

$q_\gamma(90\%)-q_\gamma(10\%)$ is the spread in expected value added (at a target firm) by the marginal top and bottom decile hedge fund activist.

Annual campaign frequency is the activist's frequency of undertaking campaigns (annually). It is defined as the total number of campaigns undertaken by the hedge fund activists during the sample period 2001 - 2018 divided by the number of years (18) in the sample period.

Market Capitalization is calculated as Total Assets (AT) + Market Value of Equity − Book Value of Equity (CEQ) − Deferred Tax Liabilities (TXDB). Here, *Market Value of Equity* is defined as the closing share price every calendar year (PRCC_C) times the shares outstanding at every calendar year end (CSHO).

Tobin's Q Ratio is calculated as $\frac{BookLeverage(DLTT)+MarketValueofEquity}{BookLeverage(DLTT)+BookValueofEquity(CEQ)}$, i.e., the ratio of the market value of firm's assets to the book value of firm's assets.

Sales is defined as calendar year sales (SALE) scaled by the lagged market value of the firm's assets, *Market Value of Assets* is calculated as Market Value of Equity + Long-term Debt (DLTT) + Preferred Stock (PSTK).

Return on Assets (ROA) is defined as earnings before interest, taxes, and depreciation (EBITDA) divided by lagged market value of the firm's assets. EBITDA is calculated as Sales (SALE) − Cost of Goods Sold (COGS) − Selling, General, & Administrative Expenses (XSGA).

Return on Equity (ROE) is defined as the target firm's current year EBITDA scaled by previous year's market value of equity.

Return on Invested Capital (ROIC) is defined as target firm's current year EBITDA scaled by previous year's total capital. Total capital is defined as Book Value of Equity (CEQ) + Long-term Debt (DLTT).

Cash Flow is defined as EBITDA + Depreciation (DP) scaled by lagged market value of the firm's assets.

Leverage is calculated as $1 - \frac{MarketValueofEquity}{MarketCapitalization}$.

Cash balance is defined as cash and cash equivalents (CHE) scaled by lagged market value of the firm's assets.

Dividend Yield is defined as total common and preferred dividend (DVC + DVP) divided by the sum of market value of equity and preferred stock (PSTK).

R&D is defined as research and development expense (XRD) scaled by lagged market value of the firm's assets.

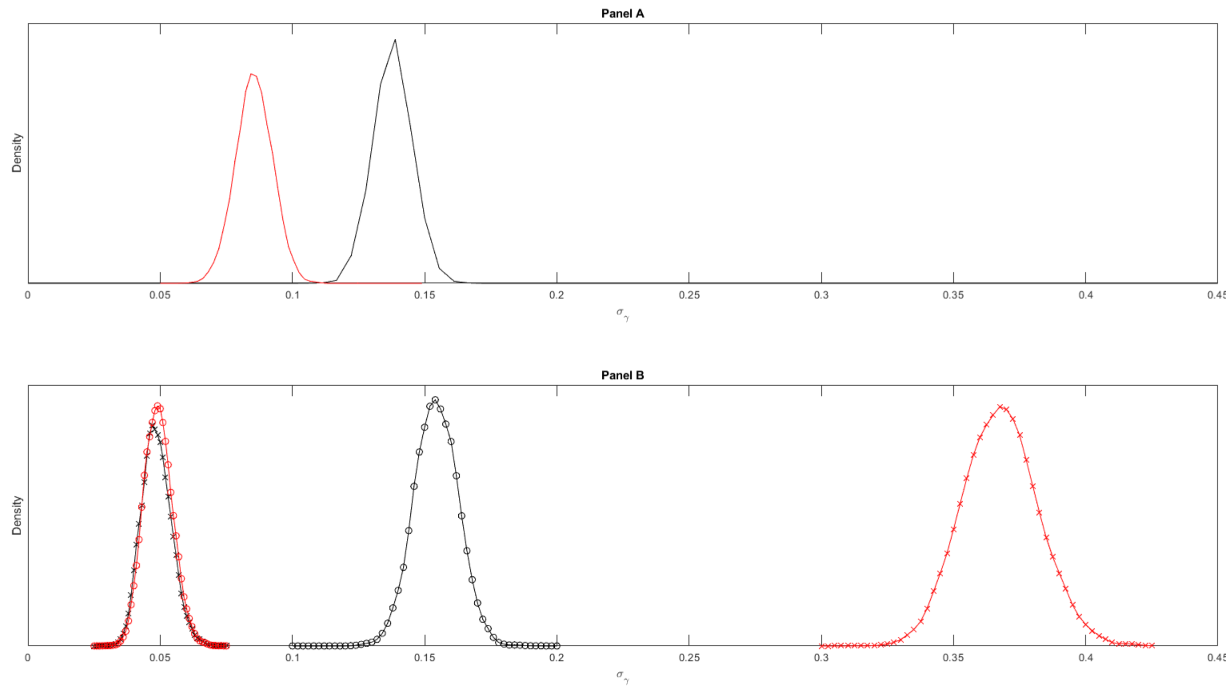

Figure A1: **Comparative Posterior Distribution of σ_γ for Extended Brav et al. (2008) Sample Vs. FactSet Sample**

This figure plots the posterior distribution of standard deviation (σ_γ) of the hedge fund-specific random effect (γ_i); estimated with the dependent variable (in the model Eq. (1)) y_{ic} as the CAR for event window $[-10, +1]$ (calculated using the Fama-French 3-Factor model) for the extended Brav et al. (2008) sample (ended 2016) vs our FactSet sample. Panel A shows the posterior distribution of σ_γ for the full sample from both data sources. The red solid line depicts the distribution of σ_γ for extended Brav et al. (2008) sample, while the black solid line depicts the distribution of σ_γ for the FactSet sample. The mean of the posterior distribution of σ_γ is 0.086 for the extended Brav et al. (2008) sample, and 0.138 for the FactSet sample. Panel B shows the posterior distribution of σ_γ for both samples split based on whether the campaign announcements are based on Schedule 13D filings or based on other news outlets. The red bubbled line depicts the distribution of σ_γ for extended Brav et al. (2008) sample where campaign announcements are based on Schedule 13D filings, while the black bubbled line depicts the same for the FactSet sample. The red crossed line depicts the distribution of σ_γ for extended Brav et al. (2008) sample where campaign announcements are based on media reports, while the black bubbled line depicts the same for the FactSet sample.

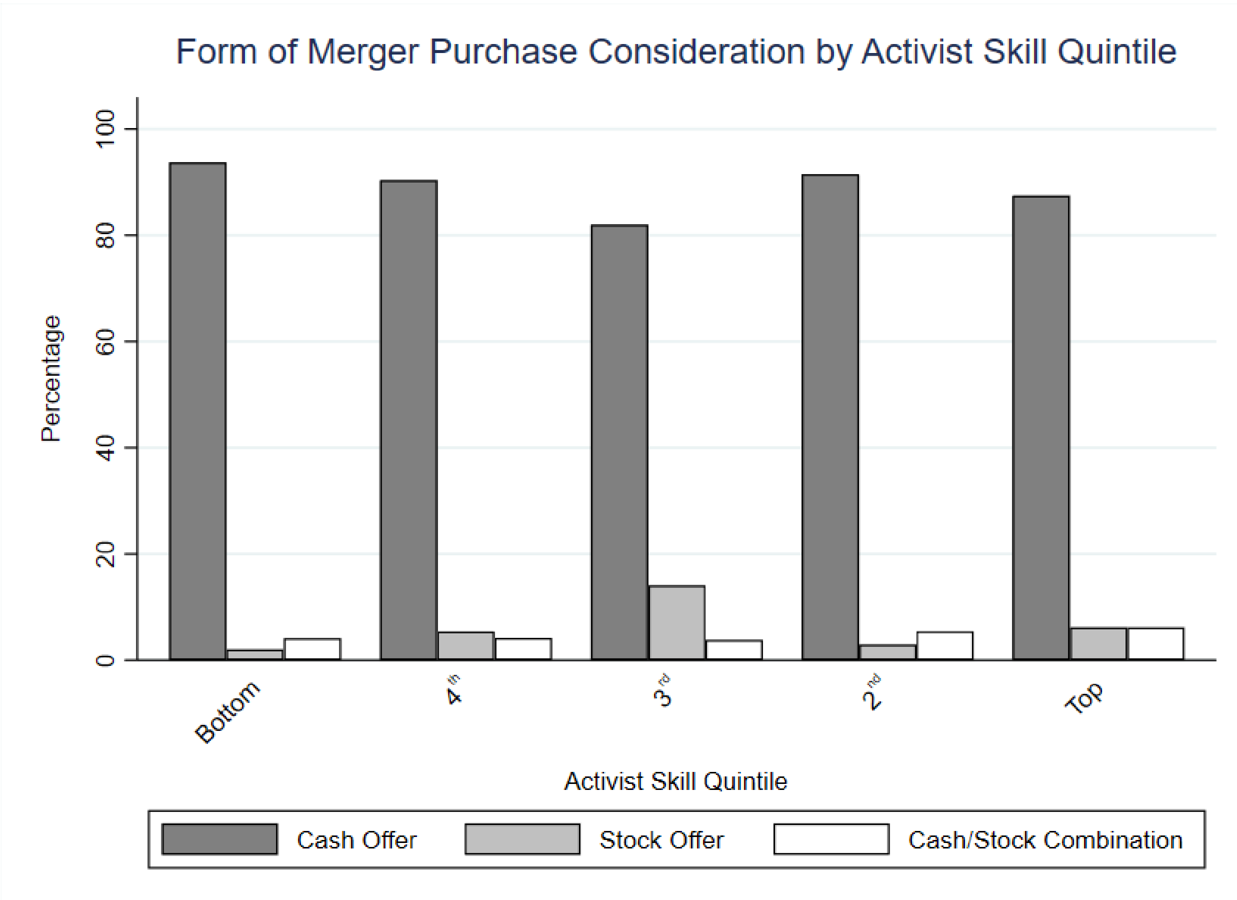

Figure A2: **Payment Type of Takeover Offer**
This figure reports statistics on payment types that are associated with a merger announcement or tender offer announcement to purchase a hedge fund activist's target firm. The sample includes all takeover announcements that are made within 3 years of the activist's initial 13D filing. Payment types are cash only offers, stock offers, and a combination of cash and stock offers. We separately report all payment type percentages by hedge fund activist skill quintile. Our sample covers the period from 2001 to 2018.

Table A1: **Out of Sample Performance of Activist Ranking based on Estimated γ vs. Activist Ranking based on Average CAR**

This table reports the results for a long-only mimicking strategy, assuming that an investor purchases shares in the same target firm as the top quintile of hedge fund activists. The ranking of activists into quintiles is based on two strategies. In the first strategy we rank the activists into quintiles based on their estimated skill (γ). This ranking is constructed every year $t-1$, based on which in year t we take long positions in the targets of the top quintile of hedge fund activists for 3-, 6-, and 9-month holding periods. Using this strategy, the mean buy-and-hold abnormal return ($\overline{BHAR}$) for each holding period in each investment year (t) are reported in Panel A. In the second strategy we rank the activists into quintiles based on the average observed CARs for each activist till year $t-1$. The returns using this strategy in each investment year (t) are reported in Panel B. The methodology for calculating $\overline{BHAR}$s and the skewness adjusted t-statistic is detailed in Appendix D.

Holding Period	3-Months		6-Months		9-Months	
Investment Year	$\overline{BHAR}$	T-Stat	$\overline{BHAR}$	T-Stat	$\overline{BHAR}$	T-Stat
Panel A: Investment in Targets of Top Quintile Activists based on Estimated γ						
2002	-1.68%	-0.1693	-0.99%	-0.0037	0.77%	0.4963
2003	-3.06%	-0.5051	-8.88%	-0.8210	-6.83%	-0.3242
2004	15.92%	1.6095	18.54%	1.3366	19.37%	1.4485
2005	-15.12%	-2.4952	-15.25%	-1.4133	-17.72%	-2.0991
2006	1.84%	0.6275	-0.98%	-0.3603	-1.14%	-0.2723
2007	9.63%	2.5963	2.76%	0.4912	3.48%	0.5472
2008	-2.13%	-0.6269	-12.07%	-2.4261	-21.89%	-4.3165
2009	5.26%	0.5983	-5.05%	-0.6012	-7.54%	-0.5192
2010	3.89%	0.6392	3.78%	0.5148	5.20%	0.7189
2011	4.11%	1.3936	7.99%	1.4251	-0.02%	0.0040
2012	13.21%	2.4743	21.50%	2.0753	23.25%	2.0283
2013	0.79%	0.2382	-0.31%	0.0407	12.20%	1.1686
2014	0.67%	0.1940	4.81%	1.2646	4.24%	0.8998
2015	10.57%	2.0730	11.13%	2.3722	31.29%	3.5126
2016	3.90%	0.6096	0.55%	0.0776	-5.59%	-0.5959
2017	-4.02%	-1.3598	-10.96%	-1.0599	-18.74%	-3.2128
2018	11.48%	2.1096	9.96%	0.9446	9.25%	0.6224
Panel B: Investment in Targets of Top Quintile Activists based on Average CAR						
2002	12.01%	-	26.29%	-	-1.73%	-
2003	-6.12%	-0.9972	-16.02%	-2.0619	-16.08%	-0.7193
2004	15.92%	1.6095	18.54%	1.3366	19.37%	1.4485
2005	-15.12%	-2.4952	-15.25%	-1.4133	-17.72%	-2.0991
2006	-3.27%	-0.7870	-8.18%	-1.7136	-5.48%	-0.7168
2007	9.94%	2.6198	3.77%	0.6399	6.10%	0.9551
2008	-12.84%	-1.5312	-27.51%	-4.0631	-39.58%	-1.9900
2009	4.02%	0.2514	0.43%	0.1440	1.61%	0.1370
2010	-1.83%	-0.5626	-0.49%	-0.1946	-1.01%	-0.2542

Continued on next page –

– continued from previous page

Holding Period	3-Months		6-Months		9-Months	
Investment Year	$\overline{BHAR}$	T-Stat	$\overline{BHAR}$	T-Stat	$\overline{BHAR}$	T-Stat
Panel B: Investment in Targets of Top Quintile Activists based on Average CAR						
2011	7.49%	-	11.18%	-	26.07%	-
2012	10.27%	0.9558	5.37%	0.4414	9.12%	0.7119
2013	12.59%	3.8626	25.19%	1.5343	57.63%	1.3480
2014	-1.75%	-0.2575	2.89%	0.2588	4.18%	0.2995
2015	-6.06%	1.2717	-14.82%	1.1099	-11.02%	1.1095
2016	5.37%	0.7179	0.15%	-0.0042	-8.58%	-0.7373
2017	-4.06%	-1.2830	-12.80%	-2.0021	-22.31%	-4.6384
2018	18.78%	2.6452	19.59%	1.1827	21.18%	0.5139

End of Table A1

Table A2: **Classification of Activist Hedge Fund Tactics**
This table presents the classification of campaign tactics employed (Column 1) by hedge fund activists into tactic groups (Column 2). Column 3 reports the percentage of all campaigns in the sample (2,054) in which the specific tactic group was employed. Since a particular campaign can employ multiple tactics from more than one tactic group, the percentage in this column sums up to more than 100%. The tactics in Column 1 are arranged in increasing order of hostility/aggressiveness, following the ordering in Panel B of Table I in Brav et al. (2008).

Employed Tactics (1)	Tactics Group (2)	% of All Events (3)
No Publicly Disclosed Activism	1	47%
Publicly Disclosed Letter to Board/Management Letter to Stockholders	2	46%
Propose Precatory Proposal Propose Binding Proposal	3	7%
Call Special Meeting Take Action by Written Consent Exempt Solicitation	4	3%
Withhold Vote for Director(s) Proxy Access Nomination Nominate Slate of Directors	5	21%
Threaten Proxy Fight	6	8%
Proxy Fight	7	20%
Lawsuit	8	4%
Unsolicited Offer Hostile Offer Tender Offer Stake Only Tender Offer Launched	9	3%

Online Appendix for *Hedge Fund Activism Skill*

A Technical details of the estimation procedure

In this appendix, we provide a more detailed description of the estimation procedure that we introduce in Section (2). As we have described before, we estimate the model in Equation (1) using a Bayesian estimator (Rossi et al., 2012). The Bayesian estimation algorithm we use to construct the joint posterior distribution of the model parameters in Equation (1) is a Markov Chain Monte Carlo (MCMC) algorithm (Korteweg, 2013; Korteweg and Sorensen, 2017). Below we describe the steps of the MCMC algorithm as they apply to estimate our model.

To begin, we rewrite Equation (1) by combining the parameter for the average cumulative abnormal return and all time-specific return components in a single parameter vector β:

$$y_{ic} = X_{ic}\beta + \gamma_{\mathbf{i}} + \epsilon_{\mathbf{ic}} \tag{13}$$

where X_{ic} is a matrix with a vector of ones as its first column (to capture the intercept α) and year indicators as its remaining columns. Thus, X_{ic} has $1+T$ columns, where T is the time span (in number of years) of our data. $\beta = [\beta_0, \beta_1, ..., \beta_T]'$ is a vector of length $1+T$, where β_0 is the estimate for the model intercept and $[\beta_1, ..., \beta_T]'$ are estimates of time fixed effects. The distributional assumptions for the random effect γ_i and the campaign-specific error term ϵ_{ic} are stated in Equations (2) and (3), i.e. $\gamma_i \sim \mathcal{N}(0, \sigma_\gamma^2)$ and $\epsilon_{ic} \sim \mathcal{N}(0, \sigma_\epsilon^2)$.

The main objective of our estimation procedure is then to estimate the parameter vector $\theta \equiv (\beta, \sigma_\gamma^2, \sigma_\epsilon^2)$ conditional on observing cumulative abnormal announcement returns y_{ic} of the hedge fund activists' campaigns, the matrix X_{ic}, and our distributional assumptions for σ_γ^2 and σ_ϵ^2. To define the joint posterior distribution of the model parameters, we first have to augment the parameter vector θ with latent values for the hedge fund-specific random effects γ_i. The joint posterior distribution of the model parameters is then defined as $f(\theta, \{\gamma_i\}|Data)$. The MCMC algorithm produces a set of draws from this joint posterior using the Gibbs sampling technique (Geman and Geman, 1984; Gelfand and Smith, 1990; Korteweg, 2013).

The implementation of the MCMC algorithm (with Gibbs sampling) makes use of the Hammersley - Clifford theorem, and splits the joint posterior $f(\theta, \{\gamma_i\}|Data)$, into three complete conditional distributions, which are then sequentially sampled from. These three conditional distributions are: 1) the distribution of the variance of the campaign-specific error term (σ_ϵ^2) and beta coefficients (β) $-$ $f(\beta, \sigma_\epsilon^2 | \sigma_\gamma^2, \{\gamma_i\}, Data)$; 2) the distribution of hedge fund-specific latent random effects (γ_i) $-$ $f(\{\gamma_i\} | \theta, Data)$; and 3) the distribution of the variance of the hedge fund-specific random effect (σ_γ^2) $-$ $f(\sigma_\gamma^2 | \beta, \sigma_\epsilon^2, \{\gamma_i\}, Data)$. We sample from each of the distributions $1-3$ sequentially, conditional on the most recent draw of the other parameters.

In the first step, sampling from the distribution of the variance of the campaign-specific error term and beta coefficients, we estimate a standard Bayesian regression. In particular, for each hedge fund activist i, the regression (likelihood) model takes the form

$$y_i - W_i \gamma i = X_i \beta + \epsilon_i \tag{14}$$

The above equation is stacked across the N hedge fund activists in the sample. Then, $y = [y_1', y_2', ..., y_N']'$ is a vector of stacked cumulative abnormal returns at the filing of a 13D for each campaign c initiated by a hedge fund activist i, across the N hedge fund activists in the sample. Thus the length of vector y is $L = \sum_{i=1}^{N} c_i$ (c_i, which is the total number of campaigns per hedge fund activist i). The matrix W, is a $L \times N$ matrix of indicator variables, with each column vector having ones in the rows corresponding to each hedge fund activist and zeros in all other rows. The vector $\gamma = [\gamma_1, \gamma_2, ..., \gamma_N]'$ is a vector of length N, containing the hedge fund-specific random effect. To reiterate, X is a matrix with a vector of ones as its first column (to capture the model intercept) and year dummy vectors as its remaining columns. Thus, matrix X is a $L \times (1+T)$ matrix, where T is the time span (in number of years) for the sample data. $\beta = [\beta_0, \beta_1, ..., \beta_T]'$ is a vector of length $1+T$, where β_0 is the estimate for the model intercept, and $[\beta_1, ..., \beta_T]'$ are estimates of time fixed effects. With the conjugate priors,

$$\sigma_\epsilon^2 \sim \mathcal{IG}(a_0, b_0) \tag{15}$$

and

$$\beta | \sigma_\epsilon^2 \sim \mathcal{N}(\mu_0, \sigma_\epsilon^2 \Sigma_0^{-1}) \tag{16}$$

The posterior distribution of the model parameters β and σ_ϵ^2 is

$$\sigma_\epsilon^2 | Data \sim \mathcal{IG}(a, b) \tag{17}$$

and

$$\beta|\sigma_\epsilon^2, Data \sim \mathcal{N}(\mu, \sigma_\epsilon^2 \Sigma^{-1}) \tag{18}$$

where

$$a = a_0 + L \tag{19}$$

$$b = b_0 + e'e + (\mu - \mu_0)'\Sigma_0(\mu - \mu_0) \tag{20}$$

$$\mu = \Sigma^{-1}(X'(y - W\gamma) + \mu_0\Sigma_0) \tag{21}$$

$$\Sigma = X'X + \Sigma_0 \tag{22}$$

$$e = y - W\gamma - X\beta \tag{23}$$

We use diffuse prior distributions (Eq. (15) and (16)) to simulate the draws from the posterior marginal distributions (Eq. (17) and (18)), so that the results are driven by our data and not our prior assumptions. As suggested by Korteweg (2013), we set the parameters of the conjugate prior in Eq. (15) to $a_0 = 2.1$ and $b_0 = 0.15^2$. This implies that the prior belief about the expected value of σ_ϵ is that $E[\sigma_\epsilon] = 0.128$ and that the 99% credible interval for σ_ϵ is 0.054 to 0.431. The parameters of the prior distribution of β (Eq. (16)) are taken as $\mu_0 = 0$ and $\Sigma_0 = \frac{1}{10{,}000} \times \mathbb{1}_{1+T}$. The matrix $\mathbb{1}_{1+T}$ is a $(1+T) \times (1+T)$ identity matrix. Thus the prior mean of $\beta = 0$ and its standard deviation is $100 \times \sigma_\epsilon$.

Given the conditioning on parameters β and σ_ϵ^2 from the previous sampling step, now we draw the hedge fund-specific random effects γ_i by estimating the following regression (likelihood) model for each hedge fund activist i:

$$y_i - X_i\beta = W_i\gamma i + \epsilon_i \tag{24}$$

Given the prior in Eq. (2), the posterior distribution of γ is;

$$\gamma|\theta, Data \sim \mathcal{N}(\mu_\gamma, \sigma_\epsilon^2 \Omega^{-1}) \tag{25}$$

where;

$$\Omega = W'W + \frac{\sigma_\epsilon^2}{\sigma_\gamma^2}\mathbb{1}_N \tag{26}$$

$$\mu_\gamma = \Omega^{-1}(W'(y - X\beta)) \tag{27}$$

$\mathbb{1}_N$ is a $N \times N$ identity matrix.

The prior distribution of γ (Eq. (2)) has a mean of zero, hence all γs are set to zero at the start of the algorithm. The parameter assumptions for the prior distribution of σ_γ^2 are discussed in the next step.

Given the conditioning on parameters β, σ_ϵ^2 and γ_i, which we have drawn in the previous two steps, we now draw the variance of hedge fund-specific random effects σ_γ^2. Using an inverse gamma prior

$$\sigma_\gamma^2 \sim \mathcal{IG}(c_0, d_0) \tag{28}$$

the posterior distribution of σ_γ^2 is

$$\sigma_\gamma^2 | \sigma_\epsilon^2, \beta, \{\gamma_i\}, Data \sim \mathcal{IG}(c, d) \tag{29}$$

where

$$c = c_0 + N \tag{30}$$

$$d = d_0 + \gamma'\gamma \tag{31}$$

Similar to what we have done before, we set the parameters of the prior distribution of σ_γ^2 (Eq. (28)) so that the prior itself is uninformative. We set the parameters of the conjugate prior in Eq. (28) to $c_0 = 2.1$ and $d_0 = 0.15^2$. This implies that the prior belief about the expected value of σ_γ is that $E[\sigma_\gamma] = 0.128$ and that the 99% credible interval for σ_γ is 0.054 to 0.431.

After each complete cycle of sampling the parameters, we repeat the sampling cycle. The resulting sequence of parameter draws forms a Markov chain, whose stationary distribution is exactly the joint posterior $f(\theta, \{\gamma_i\}|Data)$. Given a sample of draws from this stationary distribution of the Markov chain, one can characterize the marginal posterior distributions of the model parameters $f(\theta|Data)$ and the hedge fund-specific random effect $f(\{\gamma_i\}|Data)$. This is the essence of the MCMC algorithm using Gibbs sampling. In our analysis, we repeat the cycle of draws $100,000$ times to simulate the posterior distributions and record every 10^{th} draw from the posterior to characterize the marginal posterior distributions of model parameters θ and $\{\gamma_i\}$.

This Bayesian estimation technique is useful in deriving the asymptotic distributions of our variance parameters and (nonlinear) functions of these parameter.

B Estimating the speed of learning

In this appendix, we describe our estimation procedure to obtain the probability described by Equation (10). To reiterate, Equation (10) describes the probability that hedge fund activist i's true value of skill, γ_i, lies above the P^{th} percentile of the distribution of γ, conditional on observing N cumulative abnormal announcement returns to campaigns of hedge fund activist i, and N cumulative abnormal announcement returns of the marginal P^{th} percentile hedge fund activist.

In order to construct that probability, we simulate a cross-section of 100 hedge fund activists that engage in 2 campaigns every year between 2001 and 2018. Hence, each of the 100 hedge fund activists undertakes a total of 36 campaigns, resulting in a simulated cross-section of $3,600$ campaigns. The cumulative abnormal announcement return for each simulated campaign is constructed according to Equation (1), using the posterior estimate of the parameter vector $\theta \equiv (\beta, \sigma_\gamma^2, \sigma_\epsilon^2)$ at the end of each of the $100,000$ Markov chains. At the end of each Markov chain, each of the 100 simulated hedge fund activists receives a random draw of γ_i from the full posterior distribution of γ_i. Similarly, at the end of each Markov chain, each of the $3,600$ simulated campaigns receive a random draw of ϵ_{ic} from the full posterior distribution of σ_ϵ. Thus, a new panel is simulated at the end of each Markov chain. This simulated panel then serves as the observed campaign history for the 100 hedge fund activists at the end of each Markov chain. Given this simulated panel, we can construct the probability described by Equation (10) for each of the 100 hedge fund activists at the end of each Markov chain over their full observed history of campaigns. We then report the average probability across the 100 simulated activists, over the $100,000$ Markov chains, for each incremental campaign (1 to 36) over the campaign history in Figure 3.

C Measuring campaign specialization

This appendix provides an example of how to calculate our third measure of campaign specialization. Let us begin by considering an activist that uses campaign tactics as described in Online Appendix Table OA2. The table reports tactic clusters, i.e. we have grouped individual tactics into the tactic clusters of Appendix Table A2. With the information of Online Appendix Table OA2, we first compute the usage frequencies for each tactic cluster across the activist's set of campaigns. In our case, the first cluster occurs once, the second cluster occurs seven times, etc. We summarize the frequencies in an array of cluster-frequency pairs: $\{(1,1),(2,7),(3,3),(4,4),(5,1),\ (6,3),(7,3),(8,3),(9,0)\}$.

In a second step, we then rank-order the array of cluster-frequency pairs and assign a rank order number to each pair. The result is an array of rank-order-number-cluster-frequency triplets: $\{(1,2,7),(2,4,4),(3,3,3),(4,6,3),(5,7,3),(6,8,3),(7,1,1),(8,5,1)\}$. For each activist, we then compute an average tactic score as the sum-product of the rank order number scores and the cluster frequencies, scaled by the sum of the cluster frequencies. In particular, for our example, the average tactics score (ATS) is:

$$\mathcal{ATS} = \frac{1\times 7 + 2\times 4 + 3\times 3 + 4\times 3 + 5\times 3 + 6\times 3 + 7\times 1 + 8\times 1}{7+4+3+3+3+3+1+1} \tag{32}$$

In the third step, we compute tactics scores (TS) for each of the activist's campaigns. These are defined as the numerator of the average tactics score, i.e. the sum-product of the rank order number scores and the cluster frequencies, computed separately for each campaign. For example, the second campaign of our activist (Campaign ID 2) gives us:

$$\mathcal{TS} = 1\times 1 + 3\times 1 + 8\times 1 + 5\times 1 = 16 \tag{33}$$

We find a tactics score for each campaign of the activist, and then calculate the sum of the squared deviations of each activist's campaign-specific tactic scores TS_c from the activist-specific average tactic score (ATS). Finally, we convert this sum of squared deviations into a standard deviation, which becomes our third measure of activist-specific campaign specialization. Higher values of the measure indicate that an activist's choice of tactics vary more from its average tactical pattern (the activist is more flexible in the means used). In contrast, smaller values of the measure indicate that the activist deviates less in its choice of tactics from its average tactical pattern (the activist uses a more standardized approach).

D Constructing buy-and-hold abnormal returns

The first step in in constructing long-term buy-and-hold abnormal returns is the construction of reference portfolios (Lyon et al. (1999)). We start with with all NYSE/AMEX/Nasdaq firms with available data on the monthly return files extracted from CRSP for the period January 1996 through December 2018. We delete the firm-month returns on securities identified by CRSP as other than ordinary common shares (CRSP share codes 10 and 11). 70 Reference portfolios are then formed on the basis of firm size and book-to-market ratios as follows.

We construct 14 size reference portfolios as follows:

1. Calculate firm size (market value of equity calculated as price per share multiplied by shares outstanding) in June of each year for all firms.

2. In June of year t, rank all NYSE firms on the basis of firm size and form size decile portfolios based on these rankings.

3. AMEX and Nasdaq firms are placed in the appropriate NYSE size decile based on their June market value of equity.

4. Then, further partition the smallest size decile, decile one, into quintiles on the basis of size rankings of all firms (without regard to exchange) in June of each year. This is done because approximately 50% of all firms fall in the smallest size decile.

Next we construct 5 book-to-market reference portfolios as follows:

1. Calculate a firm's book-to-market ratio using the book value of common equity (ceqq) divided by the market value of common equity in December of year $t-1$.

2. Each size portfolio is then further partitioned into five book-to-market quintiles (without regard to exchange) in June of year t, based on the $t-1$ book-to-market ratios of the constituent firms of respective size deciles.

Once the universe of firms is sorted in these 70 buckets, we calculate 3-, 6-, and 9-month buy-and-hold returns for the size and book-to-market reference portfolios. This involves first compounding the returns on individual securities constituting the portfolio and then summing across securities.

$$R^{bh}_{ps\tau} = \sum_{i=1}^{n_s} \frac{\left[\prod_{t=s}^{s+\tau}(1+R_{it})\right]-1}{n_s} \tag{34}$$

where $R^{bh}_{ps\tau}$ is the buy-and-hold return for reference portfolio p in month s for holding period τ, R_{it} is the return for portfolio security i at time t ($s <= t <= \tau$) and n_s is the number of securities in the reference portfolio in month s. Calculating buy-and-hold abnormal returns in this fashion removes the the new listing and rebalancing biases (as discussed in Barber and Lyon (1997), Kothari and Warner (1997)).

Then the long-horizon buy-and-hold abnormal returns are calculated for each target firm in the activist campaign sample as:

$$AR_{i\tau} = R_{i\tau} - R^{bh}_{pi\tau} \tag{35}$$

where $R^{bh}_{pi\tau}$ is the buy-and-hold return (over holding period τ) on a size/book-to-market reference portfolio for target firm i; $R_{i\tau}$ is the buy-and-hold return for target firm i over holding period τ and $AR_{i\tau}$ is the buy-and-hold abnormal return from holding this target firm for a period τ. All these return variables are calculated for every month s in the sample data.

Using the buy-and-hold abnormal return $AR_{i\tau}$ for each target firm in the activist campaign sample, we can calculate the average buy-and-hold abnormal return ($\overline{BHAR}$) as:

$$\overline{BHAR}_{m\tau} = \frac{1}{n_m} \sum_{i=1}^{n_m} AR_{im\tau} \tag{36}$$

where $\overline{BHAR}_{m\tau}$ is the average buy-and-hold abnormal return (over holding period τ) for all campaigns that are initiated by the top quintile activists in year (t); $AR_{im\tau}$ is the individual buy-and-hold abnormal return (over holding period τ) for target firms of top quintile activists in year (t) and n_m is the total number of campaigns initiated by the top quintile activists in year (t). In this way we calculate the 3-, 6-, and 9-month average buy-and-hold abnormal return $\overline{BHAR}_{m\tau}$ for activist campaigns that are initiated by the top quintile activists in year (t).

The ranking of activists into quintiles is based on two strategies. In the first strategy we rank the activists into quintiles based on their skill (γ) estimated using the Markov Chain Monte Carlo (MCMC) Bayesian estimation algorithm. The estimated γ used for this ranking is based on $CAR[-10, +1]$ using the "Fama-French 3-Factor Model". This ranking is constructed every year ($t-1$) based on all available data till that year ($t-1$). In the second strategy we rank the activists into quintiles based on the average CAR for each activist. The average CARs are the $CAR[-10, +1]$ using the "Fama-French 3-Factor Model". This ranking is also constructed every year $(t-1)$ based on all available data till that year $(t-1)$.

Barber and Lyon (1997) document that long-horizon buy-and-hold abnormal returns are positively skewed, which causes t-statistics to be negatively biased. To eliminate this skewness bias Lyon et al. (1999) suggest the use of a bootstrapped skewness-adjusted t-statistic to test the significance of the average buy-and-hold abnormal return $\overline{BHAR}_{m\tau}$.

The skewness-adjusted t-statistic, t_{sa}, (developed by Johnson (1978)), is calculated as:

$$t_{sa} = \sqrt{n_m}\left(S + \frac{1}{3}\hat{\gamma}S^2 + \frac{1}{6n_m}\hat{\gamma}\right) \tag{37}$$

where

$$S = \frac{\overline{BHAR}_{m\tau}}{\sigma_{(AR_{im\tau})}}$$

$$\hat{\gamma} = \frac{\sum_{i=1}^{n_m}(AR_{im\tau} - \overline{BHAR}_{m\tau})^3}{n_m\sigma^3_{(AR_{im\tau})}}$$

and, $\sigma_{(AR_{im\tau})}$ is the cross-sectional sample standard deviation of abnormal returns for the sample of n_m firms.

Lyon et al. (1999) document that the bootstrapped application of this skewness-adjusted t-statistic yields well specified test statistics. Bootstrapping the t-statistic involves drawing $1,000$ resamples, of size $n_b = n_m/4$, from the original sample. The skewness-adjusted t-statistic (t_{sa}) is then calculated for each of these $1,000$ bootstrapped resamples. Next, the critical values (x_l^* and x_u^*), for the skewness-adjusted t-statistic (t_{sa}), to reject the null hypothesis that the average long-run buy-and-hold abnormal return $(\overline{BHAR}_{m\tau})$ is zero, at the α significance level, are determined. These critical values are ascertained from the distribution of the $1,000$ values of the skewness-adjusted t-statistic calculated for each of the $1,000$ bootstrapped resamples, by solving the equation below:

$$Pr[t_{sa}^{bootstrapped} \leq x_l^*] = Pr[t_{sa}^{bootstrapped} \geq x_u^*] = \frac{\alpha}{2} \tag{38}$$

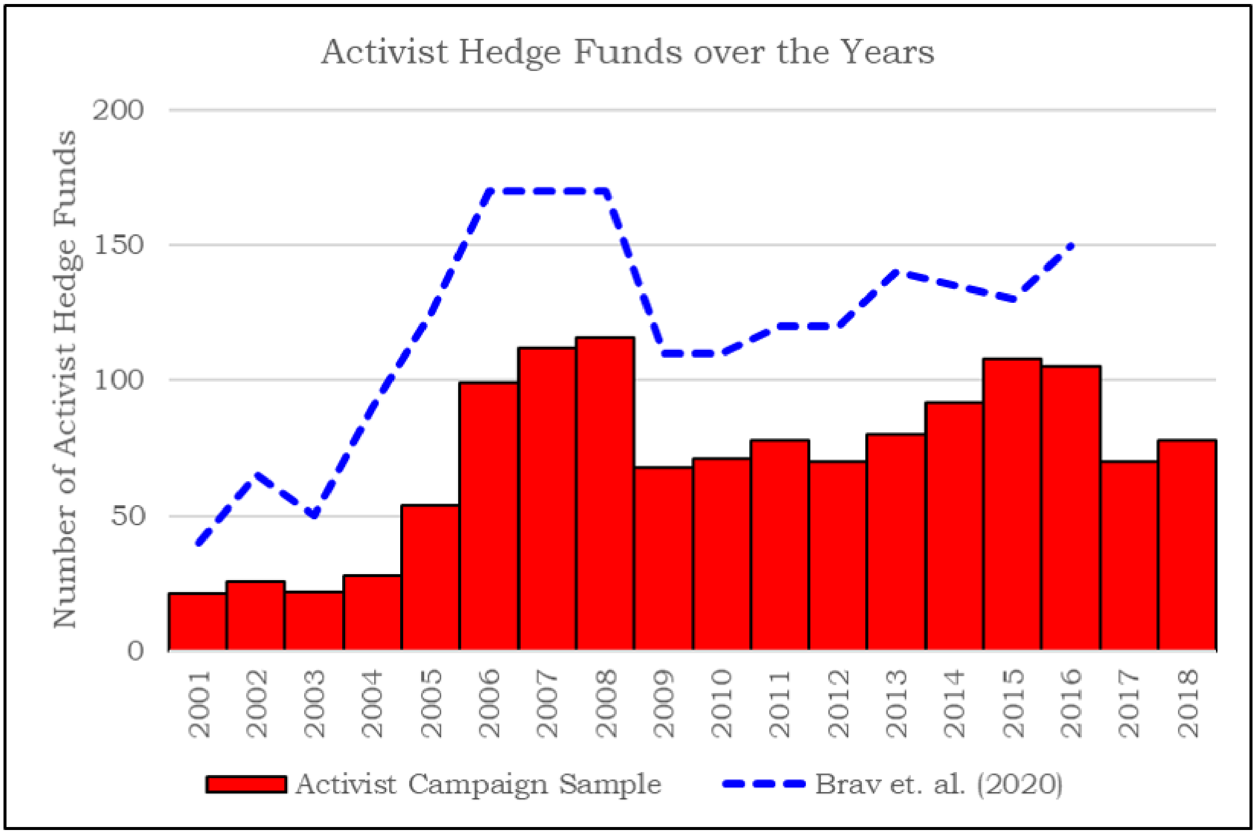

Figure OA1: **Number of Hedge Fund Activists per Year**
This figure compares the annual number of hedge fund activist between our sample and a sample that uses the same data collection procedure and estimation methods as in Brav et al. (2008) and Brav et al. (2010). This updated sample is provided on Alon Brav's website. The bar chart represents our sample, which is based on Shark Repellent's hedge fund activism data from 2001 - 2018. Each activist in our sample initiates at least one campaign in a given year, which we observe through the respective Schedule 13D filing. The dashed line represents the updated sample of Brav et al. (2008) and Brav et al. (2010), which is available from 2001 to 2016.

Table OA1: **Cumulative Average Abnormal Returns ($CAAR$) for Hedge Fund Activists**

This table reports the (observed) distribution characteristics of the average cumulative abnormal return ($CAAR$) across all campaigns undertaken by each of the 413 hedge fund activists in the sample. In Panel A $CAAR$s are based on cumulative abnormal returns (CARs) calculated using the "Market Model" of expected returns. In Panel B $CAAR$s are based on cumulative abnormal returns (CARs) calculated using the "Market-Adjusted Model" of expected returns. The $CAAR$s are reported for the event windows $[-1, +1]$, $[-10, +1]$, $[-10, +5]$, and $[-20, +20]$. Column 2 gives the number of observations (N). Columns 3 and 4 report the mean and standard deviation; Columns 5 through 11 give the 1^{st}, 10^{th}, 25^{th}, Median, 75^{th}, 90^{th} and 99^{th} percentiles for the distribution of $CAAR$s.

Variable (1)	N (2)	Mean (3)	Std. (4)	1% (5)	10% (6)	25% (7)	50% (8)	75% (9)	90% (10)	99% (11)
Panel A: Cumulative Average Abnormal Return [CAAR] - Market Model										
$CAAR[-1, +1]$	413	3.96%	15.89%	-17.06%	-2.78%	0.17%	2.34%	5.77%	11.20%	34.15%
$CAAR[-10, +1]$	413	4.61%	21.24%	-54.13%	-8.89%	-1.27%	3.56%	9.25%	18.93%	41.36%
$CAAR[-10, +5]$	413	5.83%	22.18%	-34.25%	-8.65%	-1.69%	4.36%	11.74%	22.37%	52.04%
$CAAR[-20, +20]$	413	7.59%	25.78%	-51.32%	-13.70%	-0.88%	6.73%	14.77%	27.08%	68.10%
Panel B: Cumulative Average Abnormal Return [CAAR] - Market Adjusted Model										
$CAAR[-1, +1]$	413	3.83%	15.84%	-16.32%	-2.84%	0.17%	2.24%	5.40%	10.23%	32.06%
$CAAR[-10, +1]$	413	3.76%	20.93%	-55.48%	-9.93%	-1.91%	3.07%	8.19%	17.78%	43.27%
$CAAR[-10, +5]$	413	4.74%	21.83%	-44.12%	-10.04%	-1.89%	3.40%	10.01%	20.40%	53.70%
$CAAR[-20, +20]$	413	5.12%	24.50%	-55.93%	-13.14%	-2.95%	4.45%	11.98%	23.47%	58.94%

Table OA2: **Example: Tactic Groups used by an Activist through its Campaigns** This table shows the different tactic groups used by an activist ("Activist ID" —1) through all its campaigns ("Campaign IDs" —1 thru 8). The particular tactic group employed by the activist in a particular campaign is indicated by "1" in the columns labeled "Cluster" —01 thru 09. If that tactic group is not employed by the activist it is indicated as "0".

		Cluster								
Activist ID	Campaign ID	01	02	03	04	05	06	07	08	09
1	1	1	0	0	0	0	0	0	0	0
1	2	0	1	1	0	1	0	1	0	0
1	3	0	1	0	1	0	1	0	1	0
1	4	0	1	0	1	0	0	0	0	0
1	5	0	1	0	0	0	1	0	0	0
1	6	0	1	1	1	0	0	1	1	0
1	7	0	1	1	1	0	0	1	1	0
1	8	0	1	0	0	0	1	0	0	0