# Online Appendix for ***Hedge Fund Activism Skill***


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## 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 $\beta$:

$$y_{ic} = X_{ic}\beta + \gamma_{\mathbf{i}} + \epsilon_{\mathbf{ic}} \tag{11}$$

where $X_{ic}$ is a matrix with a vector of ones as its first column (to capture the intercept $\alpha$) 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 $\beta_0$ 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 $\gamma_i$ and the campaign-specific error term $\epsilon_{ic}$ 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 $\sigma_\gamma^2$ and $\sigma_\epsilon^2$. To define the joint posterior distribution of the model parameters, we first have to augment the parameter vector $\theta$ with latent values for the hedge fund-specific random effects $\gamma_i$. 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 ($\sigma^2_\epsilon$) and beta coefficients ($\beta$) $-$ $f(\beta, \sigma^2_\epsilon|\sigma^2_\gamma, \{\gamma_i\}, Data)$; 2) the distribution of hedge fund-specific latent random effects ($\gamma_i$) $-$ $f(\{\gamma_i\}|\theta, Data)$; and 3) the distribution of the variance of the hedge fund-specific random effect ($\sigma^2_\gamma$) $-$ $f(\sigma^2_\gamma|\beta, \sigma^2_\epsilon, \{\gamma_i\}, Data)$. 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

$$y_i - W_i \gamma i = X_i \beta + \epsilon_i \tag{12}$$

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 $\beta_0$ is the estimate for the model intercept, and $[\beta_1, ..., \beta_T]'$ are estimates of time fixed effects. With the conjugate priors,

$$\sigma_\epsilon^2 \sim \mathcal{IG}(a_0, b_0) \tag{13}$$

and

$$\beta|\sigma_\epsilon^2 \sim \mathcal{N}(\mu_0, \sigma_\epsilon^2 \Sigma_0^{-1}) \tag{14}$$

The posterior distribution of the model parameters $\beta$ and $\sigma_\epsilon^2$ is

$$\sigma_\epsilon^2|Data \sim \mathcal{IG}(a, b) \tag{15}$$

and

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

where

$$a = a_0 + L \tag{17}$$

$$b = b_0 + e'e + (\mu - \mu_0)'\Sigma_0(\mu - \mu_0) \tag{18}$$

$$\mu = \Sigma^{-1}(X'(y - W\gamma) + \mu_0 \Sigma_0) \tag{19}$$

$$\Sigma = X'X + \Sigma_0 \tag{20}$$

$$e = y - W\gamma - X\beta \tag{21}$$

We use diffuse prior distributions (Eq. (13) and (14)) to simulate the draws from the posterior marginal distributions (Eq. (15) and (16)), 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. (13) to $a_0 = 2.1$ and $b_0 = 0.15^2$. This implies that the prior belief about the expected value of $\sigma_\epsilon$ is that $E[\sigma_\epsilon] = 0.128$ and that the 99% credible interval for $\sigma_\epsilon$ is 0.054 to 0.431. The parameters of the prior distribution of $\beta$ (Eq. (14)) 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 $\beta$ and $\sigma_\epsilon^2$ from the previous sampling step, now we draw the hedge fund-specific random effects $\gamma_i$ by estimating the following regression (likelihood) model for each hedge fund activist i:

$$y_i - X_i\beta = W_i\gamma i + \epsilon_i \tag{22}$$

Given the prior in Eq. (2), the posterior distribution of $\gamma$ is;

$$\gamma|\theta, Data \sim \mathcal{N}(\mu_\gamma, \sigma_\epsilon^2\Omega^{-1}) \tag{23}$$

where;

$$\Omega = W'W + \frac{\sigma_\epsilon^2}{\sigma_\gamma^2}\mathbb{1}_N \tag{24}$$

$$\mu_\gamma = \Omega^{-1}(W'(y - X\beta)) \tag{25}$$

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

The prior distribution of $\gamma$ (Eq. (2)) has a mean of zero, hence all $\gamma$s are set to zero at the start of the algorithm. The parameter assumptions for the prior distribution of $\sigma_\gamma^2$ are discussed in the next step.

Given the conditioning on parameters $\beta$, $\sigma_\epsilon^2$ and $\gamma_i$, which we have drawn in the previous two steps, we now draw the variance of hedge fund-specific random effects $\sigma_\gamma^2$. Using an inverse gamma prior

$$\sigma_\gamma^2 \sim \mathcal{IG}(c_0, d_0) \tag{26}$$

the posterior distribution of $\sigma_\gamma^2$ is

$$\sigma_\gamma^2|\sigma_\epsilon^2, \beta, \{\gamma_i\}, Data \sim \mathcal{IG}(c, d) \tag{27}$$

where

$$c = c_0 + N \tag{28}$$

$$d = d_0 + \gamma'\gamma \tag{29}$$

Similar to what we have done before, we set the parameters of the prior distribution of $\sigma_\gamma^2$ (Eq. (26)) so that the prior itself is uninformative. We set the parameters of the conjugate prior in Eq. (26) to $c_0 = 2.1$ and $d_0 = 0.15^2$. This implies that the prior belief about the expected value of $\sigma_\gamma$ is that $E[\sigma_\gamma] = 0.128$ and that the 99% credible interval for $\sigma_\gamma$ 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 $\theta$ 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, $\gamma_i$, lies above the $P^{th}$ percentile of the distribution of $\gamma$, 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 $\gamma_i$ from the full posterior distribution of $\gamma_i$. Similarly, at the end of each Markov chain, each of the $3,600$ simulated campaigns receive a random draw of $\epsilon_{ic}$ from the full posterior distribution of $\sigma_\epsilon$. 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 A1. 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:

$$\mathcal{ATS} = \frac{1\times 7 + 2\times 4 + 3\times 3 + 4\times 3 + 5\times 3 + 6\times 3 + 7\times 1 + 8\times 1}{7+4+3+3+3+3+1+1} \tag{30}$$

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:

$$\mathcal{TS} = 1\times 1 + 3\times 1 + 8\times 1 + 5\times 1 = 16 \tag{31}$$

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.

$$R^{bh}_{ps\tau} = \sum_{i=1}^{n_s} \frac{\left[\prod_{t=s}^{s+\tau}(1+R_{it})\right] - 1}{n_s} \tag{32}$$

where $R^{bh}_{ps\tau}$ is the buy-and-hold return for reference portfolio $p$ in month $s$ for holding period $\tau$, $R_{it}$ 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:

$$AR_{i\tau} = R_{i\tau} - R^{bh}_{pi\tau} \tag{33}$$

where $R^{bh}_{pi\tau}$ is the buy-and-hold return (over holding period $\tau$) 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 $\tau$ and $AR_{i\tau}$ is the buy-and-hold abnormal return from holding this target firm for a period $\tau$. 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:

$$\overline{BHAR}_{m\tau} = \frac{1}{n_m}\sum_{i=1}^{n_m} AR_{im\tau} \tag{34}$$

where $\overline{BHAR}_{m\tau}$ is the average buy-and-hold abnormal return (over holding period $\tau$) 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 $\tau$) 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 $(\gamma)$ estimated using the Markov Chain Monte Carlo (MCMC) Bayesian estimation algorithm. The estimated $\gamma$ 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 $CAR$s 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:

$$t_{sa} = \sqrt{n_m}\left(S + \frac{1}{3}\hat{\gamma}S^2 + \frac{1}{6n_m}\hat{\gamma}\right) \tag{35}$$

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 $\alpha$ 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:

$$Pr[t_{sa}^{bootstrapped} \leq x_l^*] = Pr[t_{sa}^{bootstrapped} \geq x_u^*] = \frac{\alpha}{2} \tag{36}$$

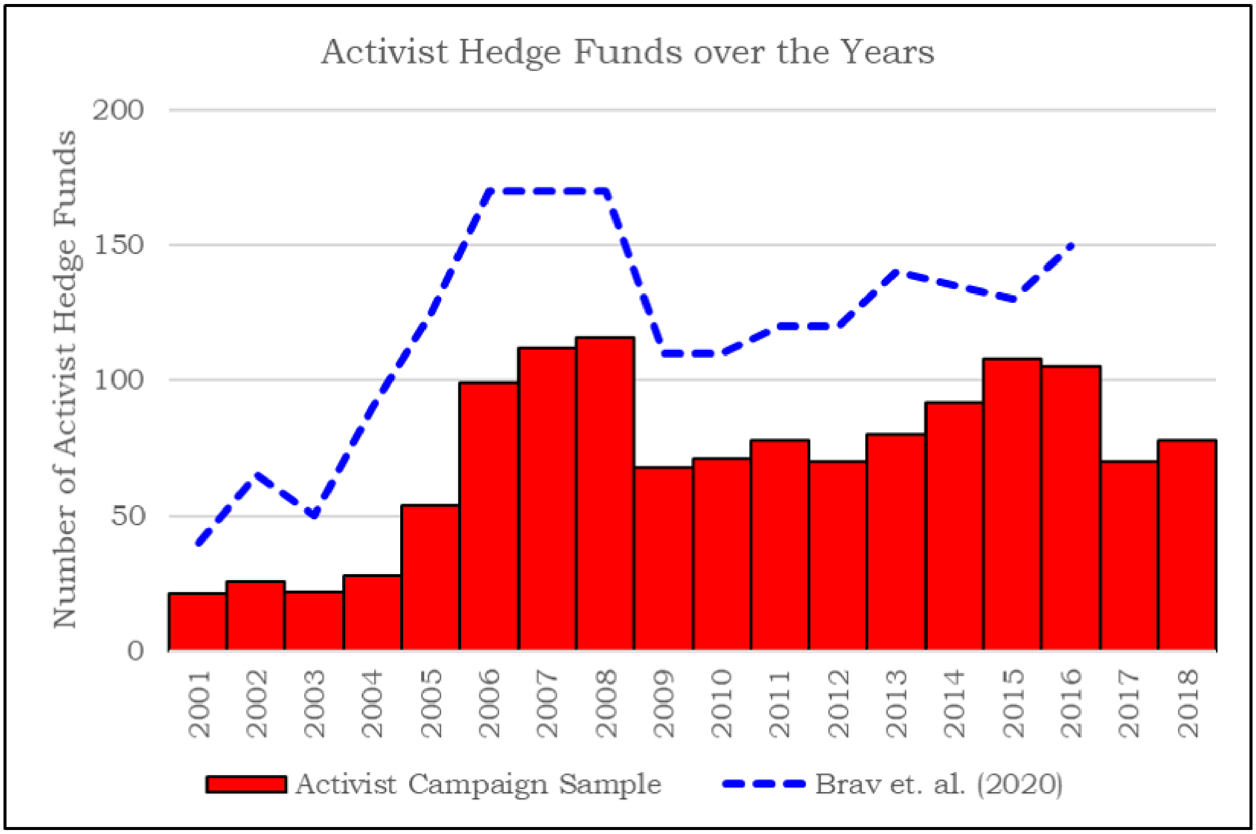


Figure OA1: **Number of Hedge Fund Activists per Year**
This figure compares the annual number of hedge fund activist between our sample and a sample that uses the same data collection procedure and estimation methods as in Brav et al. (2008) and Brav et al. (2010). This updated sample is provided on 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 ($CAR$s) calculated using the "Market Model" of expected returns. In Panel B $CAAR$s are based on cumulative abnormal returns ($CAR$s) 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 |