Online Appendix

"How does hedge fund activism reshape corporate innovation?"

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This Online Appendix provides supplemental and robustness tests to accompany the results in the paper.

Appendix 1. Supplementary tables

Appendix 1. Supplementary tables

Table A1. Patent litigation activities of target firms

This table documents the dynamics of patent litigation cases around hedge fund interventions. We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(Post_{i,t}) \times I(Target_i) + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t} .$$

The sample includes hedge fund target and control firms as described in Table 2. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). The dependent variable is the number of patent litigation cases initiated by a firm in each year. To capture a patent's litigation status, we obtain data from Lex Machina, Derwent LitAlert, and RPX database. In column (1) we include firm fixed effects, and in column (2) we include industry fixed effects. Control variables include the natural logarithms of firm market capitalization and firm age. Both specifications include year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Number of New Patent Litigation Cases	
I(Target) × I(Post)	-0.022	0.017
	(-0.561)	(0.462)
I(Target)		0.014
		(0.536)
I(Post)	0.011	0.005
	(0.291)	(0.183)
ln(MV)	0.006	0.035***
	(0.435)	(5.295)
ln(Age)	-0.066	-0.024*
	(-1.551)	(-1.868)
Constant	-0.000	0.000***
	(-1.448)	(4.812)
Observations	9,817	9,817
R-squared	0.316	0.140
Year FE	Yes	Yes
Firm FE	Yes	No
Industry FE	No	Yes

Table A2. Hedge funds' investment horizon (in days)

This table provides the length of holding period (in number of days) at different percentiles of the sample. The sample is based on hedge fund targets for which we can define an "exit" event. We use multiple sources to determine the "exit date" when the hedge fund significantly reduces its investment in the target company. First, we retrieve from Thomson Financial 13(f) quarterly holdings data for the first quarter-end when the hedge fund's stake in the target company drops below 3%. We define "exit date" in this case the middle date in that quarter (roughly quarter-end date minus 90 days). When such information is not available, we use the hedge fund's last Schedule 13D/A filing date to determine when its ownership in the target firm drops below the 5% disclosure threshold. Finally, we supplement this information with news searches for other forms of exit (such as a delisting of the company). These combined data sources allow us to form estimates of the hedge fund's investment duration after the filing of their initial Schedule 13D. The summary statistics below are reported for the innovative sample and the non-innovative sample separately, as defined in the paper. The innovative sample includes all firms that filed and were granted at least one patent before the hedge fund intervention and have at least one positive R&D expenditure within the five-year window prior to the intervention.

	Innovative Sample	Non-Innovative Sample
5^{th}	161	115
25^{th}	420	325
50^{th}	717	669
75^{th}	1299	1251
95^{th}	2673	2563
Mean	982	893

Table A3. Innovation subsequent to hedge fund activism—long and short holding duration

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + [\beta_1^S, \beta_1^M, \beta_1^L] \cdot I\left(Post_{i,t}\right) \times I(Target_i) \times \begin{bmatrix} I(ShortDuration_i) \\ I(MediumDuration_i) \\ I(LongDuration_i) \end{bmatrix} + \beta_2 \cdot I(Post)$$

$$+\gamma \cdot Control_{i,t} + \varepsilon_{i,t} \,.$$

The sample includes hedge fund target and control firms as described in Table 2. We include observations from 5 years prior to and 5 years post intervention for both the target and matched firms. *I(LongDuration), I(MediumDuration),* and *I(ShortDuration)* are dummy variables indicating if the firm is targeted and held by a hedge fund activist for the categorized length of durations (sorted into terciles). *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1) and (2) the dependent variable is R&D expenditures scaled by firm assets. In columns (3) and (4) the dependent variables is the natural logarithm of patent counts (plus one). In columns (5) and (6) the dependent variable is the natural logarithm of citations per patent (plus one). Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics. based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	R&D/Assets (%)		Log (1+# New Patents)		Log (1+Ave.Citations)	
I(Target) × I(Post)	-0.151		0.155***		0.151***	
	(-1.323)		(3.071)		(3.711)	
I(Target) × I(Post) × *Short-duration*		-0.342		0.117**		0.130*
		(-1.583)		(1.979)		(1.704)
I(Target) × I(Post) × *Medium-duration*		-0.177		0.148**		0.181**
		(-0.940)		(2.428)		(2.260)
I(Target) × I(Post) × *Long-duration*		-0.160		0.175***		0.153**
		(-1.000)		(3.337)		(2.437)
I(Post)	0.061	0.061	-0.060*	-0.060*	0.007	0.007
	(0.430)	(0.430)	(-1.935)	(-1.935)	(0.176)	(0.176)
ln(MV)	-0.580***	-0.580***	0.047***	0.047***	0.048***	0.048***
	(-13.736)	(-13.736)	(4.076)	(4.076)	(3.310)	(3.310)
ln(Age)	0.014	0.014	-0.029	-0.029	-0.084	-0.084
	(0.108)	(0.108)	(-0.747)	(-0.747)	(-1.506)	(-1.506)
Constant	8.872***	8.872***	-0.009	-0.009	0.432	0.432
	(7.347)	(7.347)	(-0.029)	(-0.029)	(1.064)	(1.064)
Observations	9,817	9,817	9,817	9,817	9,817	9,817
R-squared	0.888	0.888	0.632	0.632	0.555	0.555
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A4: Calendar-time portfolio regressions, innovative firms

This table presents calendar-time portfolio regressions in which innovative event firms are grouped into a portfolio that is traded in calendar-time and we estimate the portfolio's abnormal performance. An "innovative" firm is defined as in Table 2 of the paper. For example, we form a [-36, -1] portfolio beginning in January 1994 by buying all firms that will be targeted by an activist hedge fund in three years' time and the firms are held until the month preceding the intervention before selling. Similarly, we form a [+1, +36] portfolio by buying all firms that were targeted by a hedge fund one month beforehand and these firms are held for three years. Portfolio return is either equal or value-weighted. For each holding period and weighting scheme we estimate a regression of the resulting portfolio excess returns on the Fama-French RMRF, SMB, and HML factors and a momentum factor, MOM. Because the number of events in our sample shows a steady increase over the sample period we estimate the regression coefficients using weighted least squares using the number of events firms in a given calendar month as weights.

"Alpha" is the estimate of the portfolio intercept. "Beta" is the factor loading on the market excess return (the Fama and French RMRF). "SMB," "HML," and "MOM" are the estimates of factor loadings on the Fama-French size and book-to-market factors, and the Carhart momentum factor, respectively. We report t-statistics below the respective point estimates. "R2" is the adjusted R2 from the regressions and "N" is the number of monthly portfolio return observations. Panel A reports the results of equal-weighted portfolios and Panel B reports the results of value-weighted portfolios. We set a minimum of ten firms per month for all portfolios.

Panel A: Equal-weight four-factor model

Event window	Alpha	Beta	SMB	HML	MOM	N	R2
[-36,-1]	-0.27	0.91	0.85	0.40	-0.24	193	85.9%
	(-1.63)	(20.83)	(19.31)	(8.32)	(-7.54)		
[+1,+36]	0.29	0.84	0.89	0.21	-0.25	192	81.2%
	(1.51)	(17.93)	(16.37)	(3.11)	(-7.51)		
[+1,+60]	0.27	0.88	0.82	0.31	-0.22	216	85.1%
	(1.43)	(22.21)	(16.66)	(7.00)	(-7.96)		

Panel B: Value-weight four-factor model

Event Window	Alpha	Beta	SMB	HML	MOM	N	R2
[-36,-1]	-1.18	1.03	0.67	0.23	-0.18	193	87.9%
	(8.99)	(26.11)	(16.36)	(4.01)	(-5.93)		
[+1,+36]	0.21	0.97	0.52	0.23	-0.02	192	85.3%
	(1.19)	(25.61)	(10.77)	(4.19)	(-0.51)		
[+1,+60]	0.12	0.93	0.37	0.29	-0.00	216	83.9%
	(0.67)	(27.72)	(8.32)	(6.22)	(0.01)		

Table A5. Innovation subsequent to hedge fund activism—strategies (business and sales of assets)

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + [\beta_1^{Strategy}, \beta_1^{Non-strategy}] \cdot I(Post_{i,t}) \times I(Target_i) \times \begin{bmatrix} I(Targeting\ Strategy) \\ I(Targeting\ Nonstrategy) \end{bmatrix} + \beta_2 \cdot I(Post) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t}\ .$$

The sample includes hedge fund targets and control firms as described in Table 2. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. *I(Targeting Strategy)* and *I(Targeting Non-strategy)* are dummy variables indicating whether the firm is targeted by hedge fund activists with objectives related to the firm's strategic development, which is typically more related to innovative activities. We categorize "strategy-focused" if the hedge fund activist explicitly claims that they focus on "business" and "sales of assets" of the target firm. *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1) and (2) the dependent variable is R&D expenditures scaled by firm assets. In columns (3) and (4) the dependent variable is the natural logarithm of patent counts (plus one). The dependent variable in column (5) and (6) is the natural logarithm of citations per patent (plus one). Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	R&D/Assets (%)		Log (1+# New Patents)		Log (1+Ave.Citations)	
I(Target) × I(Post)	-0.151		0.155***		0.151***	
	(-1.323)		(3.071)		(3.711)	
Activism on Business Strategy		-0.177		0.181***		0.144*
		(-0.517)		(3.275)		(1.915)
Activism mainly on Non-Strategy		-0.142		0.146***		0.161***
		(-0.306)		(3.006)		(2.918)
I(Post)	0.061	0.061	-0.060*	-0.060*	0.007	0.007
	(0.430)	(0.430)	(-1.935)	(-1.935)	(0.176)	(0.176)
ln(MV)	-0.580***	-0.580***	0.047***	0.047***	0.048***	0.048***
	(-13.736)	(-13.736)	(4.076)	(4.076)	(3.310)	(3.310)
ln(Age)	0.014	0.014	-0.029	-0.029	-0.084	-0.084
	(0.108)	(0.108)	(-0.747)	(-0.747)	(-1.506)	(-1.506)
Constant	8.872***	8.872***	-0.009	-0.009	0.432	0.432
	(7.347)	(7.347)	(-0.029)	(-0.029)	(1.064)	(1.064)
Observations	9,817	9,817	9,817	9,817	9,817	9,817
R-squared	0.888	0.888	0.632	0.632	0.555	0.555
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A6. Innovation subsequent to hedge fund activism—extension to Table 3 using target firms with a minimum of five patents

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(Post_{i,t}) \times I(Target_i) + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t} .$$

We employ the sample of hedge fund targets and matched firms, retaining only those innovative target firms who file for at least five patents before the event and their matched firms. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1) the dependent variable is R&D expenditures scaled by firm assets while in column (2) the dependent variable is raw R&D expenditures. In columns (3) and (4) the dependent variables are the natural logarithm of patent counts (plus one) and the natural logarithm of citations per patent (plus one), respectively. In columns (5) and (6) the dependent variables are the patent generality and originality scores, respectively, both described in Appendix 1. In column (7) the dependent variable is the market value of new patents applied during the year, calculated as the market responses to the patents' approval following Kogan et al. (2015). Control variables include the natural logarithm of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	R&D/Assets (%)	R&D Expenses ($ mil)	ln(1+# New Patents)	ln(1+Ave.Citations)	Originality	Generality	Yearly Innovation Value ($M)
I(Target) × I(Post)	-0.073	-15.614***	0.160***	0.155***	0.029**	0.012	15.071**
	(-0.547)	(-3.126)	(3.687)	(2.701)	(2.306)	(1.004)	(2.022)
I(Post)	-0.195	6.720	-0.051	0.032	-0.053***	-0.000	-3.559
	(-1.234)	(1.138)	(-1.428)	(0.679)	(-3.482)	(-0.004)	(-0.476)
ln(MV)	-0.763***	7.330***	0.047***	0.036**	0.010**	0.007	0.121
	(-14.875)	(3.831)	(3.601)	(1.999)	(2.107)	(1.620)	(0.058)
ln(Age)	-0.001	-8.530	0.001	-0.103*	-0.024	0.018	13.078**
	(-0.004)	(-1.518)	(0.014)	(-1.780)	(-1.631)	(1.232)	(2.100)
Constant	10.937***	15.711	0.264	1.241**	0.379**	0.099	-9.523
	(7.550)	(0.291)	(0.618)	(2.173)	(2.277)	(0.915)	(-0.112)
Observations	6,993	6,993	6,993	6,993	2,438	2,146	2,438
R-squared	0.901	0.910	0.672	0.598	0.525	0.483	0.613
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A7. Negative binomial analysis on patent number/citations after hedge fund activism

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(Post_{i,t}) \times I(Target_i) + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t}\ .$$

We employ the sample of hedge fund targets and matched firms as described in Table 2. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. I(Target) is a dummy variable indicating whether the firm is a target of hedge fund activism, I(Post) is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1), the dependent variable is patent counts applied for by firm i in year t. In column (2), the dependent variable is patent citations of patents applied for by firm i in year t. Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed effect dummies. The models are estimated using Maximum Likelihood and the t-statistics, based on asymptotic standard errors, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) New Patent Counts	(2) Patent Citations
I(Target) × I(Post)	0.098**	0.161**
	(2.538)	(2.514)
I(Post)	0.008	0.056
	(0.307)	(1.386)
ln(MV)	0.149***	0.087***
	(28.576)	(9.544)
ln(Age)	-0.067***	-0.164***
	(-6.423)	(-10.352)
Incidence Rate Ratio	1.103**	1.175**
Observations	9,817	9,817
Year FE	Yes	Yes
Firm FE	Yes	Yes

Table A8. Innovation subsequent to hedge fund activism--extension to Table 3 using the subsample of activism events 1994-2002

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions using the same regression specification as in Table 3. We employ the sample of hedge fund targets that were targeted over the period 1994-2002 and their matched firms. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1) the dependent variable is R&D expenditures scaled by firm assets while in column (2) the dependent variable is raw R&D expenditures. In columns (3) and (4) the dependent variables are the natural logarithm of patent counts (plus one) and the natural logarithm of citations per patent (plus one), respectively. In columns (5) and (6) the dependent variables are the patent generality and originality scores, respectively, both described in Appendix 1. In column (7) the dependent variable is the market value of new patents applied during the year, calculated as the market responses to the patents' approval following Kogan et al. (2015). Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	R&D/Assets (%)	R&D Expenses ($ mil)	ln(1+# New Patents)	ln(1+Ave.Citations)	Originality	Generality	Yearly Innovation Value ($M)
I(Target) × I(Post)	-0.049	-1.583	0.173***	0.222**	0.034*	0.026	9.173
	(-0.284)	(-0.412)	(3.047)	(2.379)	(1.837)	(1.402)	(1.555)
I(Post)	0.108	-4.832	-0.080	-0.086	-0.071	-0.021	-8.119
	(0.575)	(-1.143)	(-0.883)	(-1.196)	(-1.576)	(-1.054)	(-0.934)
ln(MV)	-0.565***	3.427***	0.049***	0.033	0.015**	0.008	-0.568
	(-9.734)	(2.631)	(3.335)	(1.339)	(2.460)	(1.405)	(-0.274)
ln(Age)	0.134	4.213	-0.030	-0.116	-0.018	-0.012	11.235**
	(0.832)	(1.164)	(-0.657)	(-1.531)	(-1.025)	(-0.780)	(2.285)
Constant	8.536***	-10.464	-0.050	0.481	0.161	0.042	-12.882
	(7.296)	(-0.399)	(-0.159)	(1.091)	(1.342)	(0.501)	(-0.099)
Observations	6,135	6,135	6,135	6,135	1,847	1,395	1,847
R-squared	0.913	0.883	0.734	0.567	0.528	0.487	0.576
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A9. Innovation subsequent to hedge fund activism : taking out 1994

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(Post) \times I(Target) + \beta_2 \cdot I(Post) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t} .$$

The sample includes hedge fund target and control firms as described in Table 2. This table differs from table 3 in the paper since we exclude events from the year 1994 from the sample. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1) the dependent variable is R&D expenditures scaled by firm assets while in column (2) the dependent variable is raw R&D expenditures. In columns (3) and (4) the dependent variables are the natural logarithm of patent counts (plus one) and the natural logarithm of citations per patent (plus one), respectively. In columns (5) and (6) the dependent variables are the patent generality and originality scores, respectively, both described in Appendix 1. In column (7) the dependent variable is the market value of new patents applied during the year, calculated as the market responses to the patents' approval following Kogan et al. (2015). Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) R&D/Assets (%)	(2) R&D Expenses ($ mil)	(3) Log (1+# New Patents)	(4) Log (1+Ave.Citations)	(5) Originality	(6) Generality	(7) Yearly Innovation Value ($M)
I(Target) × I(Post)	-0.154	-11.105***	0.152***	0.156***	0.026***	0.010	12.549*
	(-1.339)	(-3.088)	(3.710)	(3.091)	(2.720)	(1.213)	(1.807)
I(Post)	0.056	4.678	-0.062*	0.006	-0.048***	-0.005	-4.635
	(0.389)	(1.040)	(-1.958)	(0.153)	(-3.868)	(-0.489)	(-0.586)
ln(MV)	-0.581***	5.387***	0.046***	0.046***	0.012***	0.009***	-0.427
	(-13.697)	(4.054)	(3.976)	(3.162)	(3.423)	(2.890)	(-0.147)
ln(Age)	0.008	-2.803	-0.028	-0.087	-0.022*	0.008	17.821**
	(0.065)	(-0.695)	(-0.719)	(-1.553)	(-1.866)	(0.735)	(2.531)
Constant	8.892***	11.223	0.356***	1.013***	0.142***	0.164***	-7.226
	(9.978)	(0.402)	(3.154)	(4.759)	(2.616)	(3.189)	(-0.150)
Observations	9,759	9,759	9,759	9,759	3,166	2,714	3,166
R-squared	0.888	0.909	0.630	0.552	0.503	0.455	0.625
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A10. Comparison of attrition rates between target and matched firms

The table provides a comparison of the rate of attrition of targets of hedge fund activism and their matched firms. We report the number of hedge fund targets and the number of control firms remaining in the sample from the year of the activist intervention through five years afterwards. Corporate delisting information is obtained from CRSP, which not only codes the timing of delisting events but also the economic reason. Total attrition is reported under column "Attrition." We also categorize delisting reasons into Acquired (delisting code 200-299), Liquidation (delisting code 400-500, 574, 584), and other reasons.

Panel A: Innovative Sample

Time	HFA Targets				Matched Firms			
	% Attrition	% Acquired	% Distress	% Other Reasons	% Attrition	% Acquired	% Distress	% Other Reasons
t+1	7.2	5.8	0.2	1.2	8.0	5.3	0.7	2.0
t+2	11.0	8.4	0.6	2.0	12.7	8.0	1.0	3.7
t+3	19.2	14.2	1.1	3.9	21.3	13.5	2.1	5.7
t+4	26.8	18.4	1.8	6.6	26.6	17.8	2.7	6.1
t+5	33.3	22.1	2.6	8.6	34.0	22.6	3.4	8.0

Panel B: Non-Innovative Sample

Time	HFA Targets				Matched Firms			
	% Attrition	% Acquired	% Distress	% Other Reasons	% Attrition	% Acquired	% Distress	% Other Reasons
t+1	16.7	11.1	2.2	3.4	13.2	7.2	2.7	3.3
t+2	28.6	19.4	2.9	6.3	23.7	12.9	3.5	7.3
t+3	36.2	24.0	4.1	8.2	33.7	18.9	4.6	10.2
t+4	44.3	27.8	4.9	11.6	40.7	23.3	5.3	12.2
t+5	50.5	31.4	5.9	13.2	46.1	26.7	6.0	13.4

Table A11. Hedge fund activism and innovation—extension to Table 4, Panel B, alternative definition of a key technology class

This table provides evidence on the output from innovation at the key technology class of a firm. A technology class is defined as key (non-key) if it ranks within the top three largest (bottom three smallest) in terms of number of patents from the firm's patent stock. We use the following specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I\left(Post_{i,t}\right) \times I(Target_i) + \beta_2 \cdot I\left(Post_{i,t}\right) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t} .$$

I(Target) is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). The results are reported for measures calculated separately for key and non-key technology classes. In columns (1) and (2), the dependent variables are constructed by counting the number and average citations of new patents in the key technology classes of a firm. In columns (3) and (4) we report on the intensity of exploration at target firms subsequent to hedge fund activism. *Explorative* (*exploitative*) measure the intensity with which a firm innovates based on knowledge new (old) to the firm. Appendix 1 contains the detailed description of these variables. Column (5) to (8) are analogous to (1) to (4) except that the measures are constructed using innovation in technology classes that we classify as non-key. Control variables include the natural logarithm of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Key Technology Classes (Top 3)				Non-key Technology Classes (Bottom 3)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(1+# New Patents)	ln(1+Ave.Citation)	Explorative	Exploitative	ln(1+# New Patents)	ln(1+Ave.Citation)	Explorative	Exploitative
I(Target) × I(Post)	0.131**	0.128**	0.028*	-0.041	0.040	0.031	-0.043	0.011
	(2.414)	(2.592)	(1.699)	(-0.905)	(0.913)	(0.632)	(-0.847)	(0.250)
I(Post)	-0.053	-0.016	-0.027*	-0.003	-0.004	-0.018	0.041	-0.002
	(-1.363)	(-0.414)	(-1.698)	(-0.061)	(-0.155)	(-0.465)	(0.918)	(-0.053)
ln(MV)	0.064***	0.046***	0.010*	-0.004	0.033***	0.047***	-0.006	-0.006
	(5.647)	(2.847)	(1.907)	(-0.272)	(2.715)	(2.862)	(-0.362)	(-0.411)
ln(Age)	-0.001	-0.137**	-0.028	-0.073**	0.153***	-0.136**	-0.084**	-0.072**
	(-0.026)	(-2.484)	(-1.499)	(-2.047)	(3.162)	(-2.466)	(-1.975)	(-2.037)
Constant	-0.276	0.519	0.235	1.224***	-0.346	0.513	1.218***	1.212***
	(-0.699)	(1.230)	(1.508)	(8.306)	(-1.069)	(1.216)	(5.591)	(9.493)
Observations	9,817	9,817	3,218	3,218	9,817	9,817	3,218	3,218
R-squared	0.587	0.473	0.553	0.520	0.646	0.476	0.565	0.520
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A12. Distance between purchased patents and the target firm's patent portfolio

This table provides evidence on the characteristics of the patents purchased by hedge fund targets and their control firms. The sample consists of all the patent transactions conducted by hedge fund targets and their matched firms (as defined in Table 2), between three years before to three years after the event year (pseudo-event year for the matched firms). The dependent variable is *Distance (Patent to Firm),* which measures the distance between the purchased patent and the firm's overall patent portfolio based on the methodology developed in Akcigit et al. (2016). The two columns vary in the value (0.33 and 0.66) of the weighting parameter ι. See the header to Table 5 for a more detailed description of this variable and the parameter, ι. Both specifications also include transaction year and firm fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) Distance Measure (ι = 0.33)	(2) Distance Measure (ι = 0.66)
I(Target) × I(Post)	-0.041*	-0.058*
	(-1.773)	(-1.751)
I(Post)	0.005	0.001
	(0.691)	(0.781)
Observations	7,359	7,359
R-squared	0.316	0.322
Year FE	Yes	Yes
Firm FE	Yes	Yes

Table A13. Summary statistics of patents sold by target and control firms

The table provides patent characteristics at the patent-level for subsamples of patents owned by innovative target and control firms as defined in Table 2. The characteristics are measured as of the year prior to the hedge fund intervention. Column (1) provides results for patents sold by target firms. Column (2) provides information for patents sold by the matched firms. In column (3) we report the characteristics for the top patents held by the matched firms, defined as patents whose citation increase over the ensuing three years ranks in the top quintile among all patents held by the matched firm. Column (4) provides information on the top patents held by the target firms, and we define their top patents analogously. Column (5) presents evidence based on target firm's patents that the target chose to retain matched to the patents sold by the target firms after the event year. The matching algorithm selects from patents owned by the target but are not sold after the activism based on patent application year, total citations received before the activism, 3-year citation trend, and the distance to the firm's technology (as used in Table 5).

	(1) Patents Sold by Target Firms	(2) Patents Sold by Non-target Firms	(3) Best Patents Retained by Control Firms	(4) Best Patents Retained by Target Firms	(5) Retained PSM-matched Patents within the Target
Distance (ι = 0.33)	0.716	0.646	0.578	0.546	0.691
Distance (ι = 0.66)	0.620	0.533	0.467	0.451	0.605
Average Annual Citations Between t-3 and t-1	0.248	0.320	0.915	0.964	0.259
Total Citations Up to t	1.022	1.274	4.766	5.212	1.138
Age	6.219	4.726	5.243	6.067	6.422
Total Lifetime Citations	6.751	3.343	15.379	17.216	4.844

Table A14. Alternative specifications of the propensity score matching meant to capture the pre-event change in performance of target firms

This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(Post_{i,t}) \times I(Target_i) + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t} .$$

We employ the sample of hedge fund targets and matched firms, retaining only those innovative target firms who file for at least five patents before the event and their matched firms. In Panel A, the control sample is formed by matching each event firm to the non-event innovative firm from the same year and the same industry (2-digit SIC) with the closest propensity score, where the propensity score is estimated using log firm size, return on assets (ROA), market-to-book ratio measured at *t-1*, and the change in the target firm market-to-book ratio measured between years *t-3* and *t-1*. In Panel B, the control sample is formed by matching each event firm to the non-event innovative firm from the same year and the same industry (2-digit SIC) with the closest propensity score, where the propensity score is estimated using log firm size, return on assets (ROA), market-to-book ratio measured at *t-1*, and the change in the target firm ROA measured between years *t-4* and *t-1*. In Panel C, the control sample is formed by matching each event firm to the non-event innovative firm from the same year and the same industry (2-digit SIC) with the closest propensity score, where the propensity score is estimated using log firm size, return on assets (ROA), market-to-book ratio measured at *t-1*, and the change in the target firm market-to-book ratio measured between years *t-4* and *t-1*. We include observations from 5 years prior to and 5 years post intervention for both the targets and matched firms. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, *I(Post)* is a dummy variable equal to one if the target firm (matched control firm) is within [t+1, t+5] years after the activism event year (the pseudo-event year). In column (1) the dependent variable is R&D expenditures scaled by firm assets while in column (2) the dependent variable is raw R&D expenditures. In columns (3) and (4) the dependent variables are the natural logarithm of patent counts (plus one) and the natural logarithm of citations per patent (plus one), respectively. In columns (5) and (6) the dependent variables are the patent generality and originality scores, respectively, both described in Appendix 1. In column (7) the dependent variable is the market value of new patents applied during the year, calculated as the market responses to the patents' approval following Kogan et al. (2015). Control variables include the natural logarithm of firm market capitalization and firm age. All specifications include firm and year fixed effects. The *t*-statistics, based on standard errors clustered at the firm level, are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	(1) R&D/Assets (%)	(2) R&D Expenses ($ mil)	(3) ln(1+# New Patents)	(4) ln(1+Ave.Citations)	(5) Originality	(6) Generality	(7) Yearly Innovation Value ($M)
Panel A: PSM – Industry, Size, ROA, M/B, M/B Lag 3							
I(Target) × I(Post)	-0.153	-13.081***	0.136***	0.141***	0.031***	0.014	15.171*
	(-1.386)	(-3.038)	(3.520)	(2.928)	(2.996)	(1.102)	(1.915)
I(Post)	0.102	4.561	-0.045*	0.003	-0.047***	-0.003	3.073
	(0.981)	(1.324)	(-1.695)	(0.106)	(-4.506)	(-0.331)	(0.469)
Panel B: PSM – Industry, Size, ROA, ROA Lag 4, M/B							
I(Target) × I(Post)	-0.143	-8.770**	0.181***	0.177***	0.026**	0.011	9.223
	(-1.271)	(-2.341)	(4.513)	(3.701)	(2.554)	(1.276)	(1.434)
I(Post)	0.078	4.156	-0.077**	0.005	-0.044***	-0.002	0.077
	(0.520)	(0.889)	(-2.380)	(0.126)	(-3.466)	(-0.211)	(0.332)
Panel C: PSM – Industry, Size, ROA, M/B, M/B Lag 4							
I(Target) × I(Post)	-0.106	-9.278***	0.163***	0.190***	0.027***	0.011	10.155*
	(-1.001)	(-2.806)	(4.563)	(4.543)	(2.794)	(1.391)	(1.705)
I(Post)	0.112	4.244	-0.052**	-0.025	-0.043***	-0.005	0.134
	(1.208)	(1.539)	(-2.014)	(-0.859)	(-3.638)	(-0.492)	(0.778)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 2. An example of an intervention seeking the reallocation of patents: Starboard Value and AOL, Inc.

On February 16, 2012, Starboard Value LP filed a Schedule 13D with the SEC indicating that it owned 5.1% of AOL, Inc. The filing included a letter that the fund had sent to the CEO and Chairman, Tim Armstrong two months earlier that reviewed each of the firm's business units (Access, Search, Advertising Network, and Display) based on publicly-available information. Starboard argued that the management and the board needed to consider various ways to enhance AOL's shareholder value, most importantly, to address the "valuation discrepancy…due to the Company's massive operating losses in its Display business, as well as continued concern over further acquisitions and investments into money-losing growth initiatives like Patch." The letter concludes with a request for direct engagement with the board in order to discuss ways to find strategic alternatives that would stabilize the company and improve its operating performance and valuation.

On February 27, 2012 Starboard filed an amendment to its Schedule 13D with a second letter explicitly focusing on AOL's portfolio of intellectual property. The letter states:

> "…in addition to the valuable assets highlighted in our December Letter, AOL owns a robust portfolio of extremely valuable and foundational intellectual property that has gone unrecognized and underutilized. This portfolio of more than 800 patents broadly covers internet technologies with focus in areas such as secure data transit and e-commerce, travel navigation and turn-by-turn directions, search-related online advertising, real-time shopping, and shopping wish list, among many others."

The hedge fund proceeded to argue that the intellectual property was underutilized by pointing that other companies were likely infringing on AOL's patents. As a result, the fund projected that the portfolio of patents would generate more than $1 billion of licensing income if properly managed. The fund also cautioned that the tax liability associated with the sale of the patents should be considered, and therefore argued for the divestiture of other high cost basis assets. To facilitate the changes, the fund proposed that five of its own directors should be elected to the board during the 2012 annual meeting.

Soon thereafter, AOL retained Evercore Partners as its financial adviser, and, in early April 2012, the company announced that it would sell more than 800 patents and related patent applications to Microsoft for $1.06 billion. The company agreed to grant Microsoft a non-exclusive license to the more than 300 patents and patent applications the company chose to retain. The agreement was reached after an open auction with multiple bids by interested companies. AOL share price increased roughly 40% over the three months following the sale of the patents.[1]

[1] For more details, see, "AOL Jumps After $1.06 Billion Patent Accord with Microsoft," by Danielle Kucera, published on www.Bloomberg.com, April 10, 2012.

Appendix 3. Identifying patent transactions

This appendix provides a detailed description of the method used to identify patent transactions following the procedure in Ma (2017). We first introduce the raw dataset on patent assignments and then present the methodology used to identify patent transactions; specifically, patent assignments other than transfers from an inventor to the firm she works at or from a subsidiary to its corporate parent.

We begin with the raw patent assignment database, downloaded from the United States Patent and Trademark Office (USPTO) patent assignment files, hosted by Google Patents. A patent assignment is the transfer of (or part of) an owner's property right in a given patent or patents, and any applications for such patents. The patent transfer may occur on its own or as part of a larger asset sale or purchase. These files contain all records of assignments made to U.S. patents from the late 1970s. The original files are then parsed and combined to serve as the starting raw dataset, including all patents assigned from an inventor to the firm, from a firm to an inventor, from one inventor (firm) to another inventor (firm).

We make use of the following information for the purpose of identifying patent transactions. First, in regards to patent assignment information, we retrieve information on the assignment date, the participating parties, including the assignee (the "buyer") and the assignor (the "seller") in a transaction, and comments on the reason for the assignment. Some important reasons include assignment of assignor's interest, security agreement, merger, and change of names. Second, in regards to patent information, we retrieve information on patent application and grant dates, identification numbers (patent number and application number), and patent title. We then merge the raw assignment data with the USPTO patent databases so as to gather additional information on the original assignee and patent technology classes. We also combine the dataset with the inventor level data maintained at Harvard Business School (HBS), which allows us to identify the inventor(s) of any given patent. Since we focus on utility patents, we remove entries regarding design patents.

Next, we standardize the names of the assignee and assignor in the raw patent assignment dataset, patent original assignee names reported in the USPTO databases, and inventor names in HBS inventor database. Specifically, we employ the name standardization algorithm developed by the NBER Patent Data Project. This algorithm standardizes common company prefixes and suffixes, strips names of punctuation and capitalization and it also isolates a company's stem name (the main body of the company name), excluding these prefixes and suffixes. We keep only assignment records of which the assignment brief is included under "assignment of assignor's interest" or "merger." That is, we remove cases when the reason for the assignment is clearly not transactions such as a "change of names."

The central part of the identification of a patent transaction uses several basic principles that predict how patent transactions appear in the data. First, the initial assignment in a patent's history is less likely to be a patent transaction. It is more likely to be an original assignment to the inventing firm. Note that this principle is more helpful on patents granted after 1980, when the raw dataset started to be systematically updated. Second, if an assignment record regards only one patent with the brief reason being "assignment of assignor's interest," it is less likely to be a transaction, as it should be rare that two parties transact only one patent in a deal (see Serrano, 2010). Third, if the assignor of an assignment is the inventor of the patent, it is less likely that this assignment is a transaction, but instead more likely to be an employee inventor who assigns the patent to her employer. Fourth, if both the assignor and assignee are corporations, it is likely that this assignment is a transaction, with the exception that the patent is transferred within a large corporation (from a subsidiary to the parent, or between subsidiaries). Based on these principles, the algorithm below is a process in which we remove cases that are unlikely to be patent transactions. The steps we take are:

1. Check if the assignment record date coincides with the original grant date of the patent (the date when the patent was first issued). If it does we label the assignment as a "non-transaction" and it is removed from the data set, otherwise we move to Step 2.

2. Check whether the patent assignment record contains only one patent and is the first record for this patent, with "assignment of assignor's interest" as the assignment reason. If the answer is in the affirmative we move to Step 3, otherwise the record is labeled as a "potential transaction" and we move to Step 4.

3. Compare the assignee in the assignment record with the assignee as of the original patent assignment in the USPTO. Similarly, compare the assignor in the assignment record with the inventor names in HBS patent database. If the assignee name coincides, or the assignor is the patent inventor(s) plus the assignee is a firm, we then categorize the assignment as a "non-transaction", and it is removed from the dataset. This constraint covers cases in which either the assignee or assignor have slightly different names across different databases, otherwise the record is labeled as a "potential transaction" and we move to Step 4.

4. Perform the analysis described in Step 3 on the "potential transaction" with one minor change: When comparing the assignee in the assignment record with the assignee as of the original patent assignment in USPTO, and when comparing the assignor in the assignment record with the inventor names in HBS patent database, we allow for spelling errors captured by Levenshtein edit distance less or equal to 10% of the average length of the two strings under comparison, and we denote this name as "roughly equal to." Then, if the assignee name roughly coincides, or the assignor is roughly the patent inventor(s) plus the assignee is a firm, then the assignment is categorized as a "non-transaction" and is removed from the data set, otherwise the record is kept as a potential "transaction" and we move to Step 5.

5. Compare the standardized names and stem names of the assignee and assignor of records in the "potential transactions." If the names coincide, this is consistent with an internal transfer and the record is labeled as a "non-transaction." If the names do not coincide the record is labeled as a "transaction."