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How does hedge fund activism reshape corporate innovation?☆

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ABSTRACT

This paper studies how hedge fund activism impacts corporate innovation. Firms targeted by activists improve their innovation efficiency over the five-year period following hedge fund intervention. Despite a tightening in research and development (R&D) expenditures, target firms increase innovation output, as measured by both patent counts and citations, with stronger effects among firms with more diversified innovation portfolios. Reallocation of innovative resources, redeployment of human capital, and change to board-level expertise all contribute to improve target firms' innovation. Additional tests help isolate the effect of intervention from alternative explanations, including mean reversion, sample attrition, voluntary reforms, or activist stock-picking.

1. Introduction

There has been an ongoing debate since at least the 1980s among academics, practitioners, and policymakers about the consequences of stock market pressure on managerial incentives to engage in innovative activities that have long-term value consequences but are not easily assessed by the market. The idea that stock market pressure

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leads to "managerial myopia" has been a recurring concern (Stein, 1988, 1989) and has evolved into a heated debate in recent years as activist hedge funds have increasingly come to dominate discussions of shareholder empowerment. The concern reached a heightened level in 2015 when Laurence Fink, the chairman and CEO of BlackRock, the world's largest institutional investor, argued that activist investors put pressure on and create incentives for corporate leaders to generate short-term gains at the expense of long-term value creation.[1]

Between 1994 and 2007, there were about 1,800 engagements by hedge fund activists in which hedge funds proposed changes to payout policy, business strategy, and corporate governance, often publicly and aggressively. Recent studies, covering both the U.S. and international markets, have documented a 5% to 7% short-term average abnormal stock return when the market first learns of the activist's intervention. Moreover, the interventions are not, on average, followed by a decline in either stock returns or operating performance over the five-year window after the arrival of the activists.[2] Yet, measurement of the long-term impact of hedge fund activism has proven challenging to evaluate due to data restrictions and methodological limitations. As a result, it has been difficult to assess claims made by opponents that activists' agendas are biased towards the pursuit of short-term stock gains at the expense of firms' long-term values.[3]

Our goal is to inform the debate by analyzing how hedge fund activism reshapes corporate innovation—arguably the most important long-term investment that firms make, but also the most susceptible to short-termism.[4] A priori, neither the direction nor the magnitude of activists' impact on overall innovative activities is clear. First, activists might have a negative impact on innovation because, as Holmstrom (1989) argues, innovative activities involve the exploration of untested and unknown approaches that have a high probability of failure with contingencies that are impossible to foresee. Given the lack of observability and predictability, the concern is that management might respond to pressure for near-term performance by adopting investment/innovation policies that are detrimental to long-term firm value. More powerful current shareholders could potentially lead to greater misalignment.[5]

Second, although managerial preferences and objectives may not be aligned with firm value maximization, the order of the relative preference is not clear a priori. Like any other investment decision, a firm should only engage in innovative activities that offer an expectation of positive net present value, and agency problems may lead to either over- or under-investment. For example, over-investment may arise if specialized investment entrenches the management (Scharfstein and Stein, 2002) or if managers derive private benefits from such activities (e.g., "grandstanding" suggested by Gompers (1996)). In such a scenario, shareholders can legitimately demand that firms spend fewer resources on innovative activities. The opposite is also plausible since agency problems may lead to under-investment: shareholders may demand higher levels of research and development (R&D) than management wants if diversified investors have more capacity to absorb innovation risk (Aghion et al., 2013).

To set the stage, we first examine innovation activities at target firms before and after hedge fund intervention, measured by both inputs (R&D expenditures) and outputs (patent quantity and quality). Consistent with previous findings that target firms reduce investment and streamline their asset base following activist intervention, we find that R&D spending drops significantly in absolute amount during the five-year window subsequent to hedge fund activism. Interestingly, there does not appear to be a reduction in output from innovation—as measured by patent counts and citation counts per patent—after the intervention. In fact, most of these measures increase significantly, on average, consistent with the idea that target firms' innovation efficiency improves after hedge fund intervention.

Next, we explore four mechanisms through which hedge fund activism reshapes targeted firms' innovation. First, the improvement in patent quantity and quality is driven by firms with a diverse portfolio of patents prior to the intervention that refocused their efforts after the arrival of activists. Moreover, the increase in innovation is concentrated in technological areas that are central to the core capabilities of target firms. This set of results constitutes preliminary evidence that firms tend to improve in-

[1] In a letter sent to chief executives of the 500 largest publicly traded U.S. companies, Fink stresses the importance of taking a long-term approach to creating value and his concern with management "...response to the acute pressure, growing with every quarter, for companies to meet short-term financial goals at the expense of building long-term value. This pressure originates from a number of sources–the proliferation of activist shareholders seeking immediate returns, ..." See blackrock.com, "Delivering long-term value - Letter to corporates," March 31, 2015.

[2] See Brav, Jiang, Partnoy, and Thomas (2008), Clifford (2008), Klein and Zur (2009), Greenwood and Schor (2009), He, Qiu, and Tang (2014), and Krishnan, Partnoy, and Thomas (2016) for U.S. companies; and Becht, Franks, Mayer, and Rossi (2009), and Becht, Franks, Grant, and Wagner (2017) for non-U.S. markets. For general information about hedge fund activism, see Brav, Jiang, and Kim (2015a).

[3] See Bebchuk, Brav, and Jiang (2015), Cremers et al. (2018), and Coffee and Palia (2016) for detailed discussions regarding the debate. Outside academia, Presidential candidate Hillary Clinton, throughout her campaign, issued sharp criticism against activists whom she viewed as promoting "quarterly capitalism" with "hit-and-run" strategies (see, e.g., https://www.bloomberg.com/politics/videos/2015-07-24/hillary-clinton-seeks-end-to-quarterly-capitalism-). The chief justice of the Delaware Supreme Court, Leo Strine, has expressed a similar view in Strine (2015).

[4] In the same letter referenced in Footnote 1, Fink argues that, "In the face of these pressures, more and more corporate leaders have responded with actions that can deliver immediate returns to shareholders, such as buybacks or dividend increases, while underinvesting in innovation, skilled workforces or essential capital expenditures necessary to sustain long-term growth."

[5] Activist hedge funds have targeted R&D policies at technology powerhouses Microsoft, Google, and Apple in recent years. See "Hedge fund activism in technology and life science companies" in the Harvard Law School Forum on Corporate Governance and Financial Regulation, April 17, 2012. Such engagements are exemplified in the recent hostile intervention by Trian Partners at DuPont, an R&D powerhouse. See "DuPont's R&D is at center of fight with activist," *The Wall Street Journal*, October 27, 2014. The fund criticized DuPont's R&D efforts, proposing that the company consider splitting its agriculture, nutrition and health, and industrial biosciences divisions from its materials businesses.

novation efficiency in the period following the intervention by allocating internal innovation capacity to key areas of expertise.

Second, hedge fund intervention is followed by a more active and efficient reallocation of outputs from innovation. Specifically, target firms sell an abnormally high number of existing patents compared to their matched peer firms, and patents sold are those that are less related to their technological expertise. Moreover, patents sold post hedge fund intervention receive a significantly higher number of citations relative to their own history and matched peers. These patterns do not appear prior to the intervention, suggesting that the higher rate of patent transactions matching peripheral patents to new and better-suited owners represent efficient reallocation of innovation outputs, a plausible channel for the observed efficiency gain.

The third mechanism involves the redeployment of innovators at target firms following the intervention. We examine the productivity, in terms of both patents filed and citations per patent, separately for inventors who stay with or leave the targeted firms and any new hires. A set of coherent patterns emerge: The inventors retained by target firms are more productive than "stayers" at non-target peers; the inventors who leave following hedge fund intervention are more productive with their new employers; and, finally, the inventors newly hired post-intervention are of similar productivity at the new firm. Combined, the reshuffling of human capital post-intervention brings about efficiency gains because the key innovative personnel are matched or re-matched to work environments where they can be more productive.

Last, we document that average managerial incentives change in the post-intervention period in a manner consistent with having more "skin in the game" and risk tolerance. New and retained top executives enjoy longer expected tenure, which helps mitigate career concerns. We also find that in the three-year period prior to activists' engagement, target CEO share ownership is essentially the same as that of CEOs at matched firms. However, CEOs at target firms see an abnormal increase in their share ownership in the three-year post-intervention period relative to the same control firms. Moreover, directors added to the boards post-activism have better credentials in general and have more technology- or industry-based experience in particular, relative to directors added to the boards of matched control firms. Our findings add to the literature (Manso, 2011; Baranchuk et al., 2014) showing that general improvement in management and governance makes firms more innovative. Several main findings discussed earlier, including innovation efficiency, the refocusing of the scope of innovation, and improvement in innovative resource allocation, may well also be the direct outcomes of a top-down reform aiming at refocusing, accountability, and efficiency.

The evidence so far does not provide conclusive identification of a causal effect due to the nonrandom selection of target firms. Since selective targeting is a key aspect of the activist investment strategy, the relevant research question in our context is whether hedge fund intervention, from shareholder campaigns to proxy contests, impacts the targets' innovation strategies beyond what would have materialized had the hedge funds accumulated the same ownership in the companies but as passive investors. In contrast to research that accomplishes identification via exogenous shocks in the treatment status, we do not take a stand on what would have happened had hedge funds been matched *randomly* to their targets, but instead aim at disentangling the effects of intervention from mere stock-picking in the chosen targets with three additional tests.

The first test addresses the specific alternative hypothesis that hedge funds select companies in which management would have implemented changes to innovation even without direct or indirect pressure from the activist. We focus on the subsample of openly confrontational interventions, which are, by definition, cases where management resisted activist demands. We find that hostile engagements show qualitatively similar changes compared with the rest of the sample. The second test assesses the counterfactual that hedge funds engage only in stock-picking rather than also adding value through intervention. Specifically, we measure the performance of firms for which hedge fund ownership (and hence stock-picking) remained constant, but the fund switched from a 13G (passive ownership) to a 13D (activist) filing status.[6] The significant improvement by target firms after the switch relative to the firms for which the hedge funds maintained a 13G filing suggests an incremental effect of intervention over stock-picking. The third test estimates the incremental value of patents filed prior to the arrival of the activists but granted shortly after the intervention relative to those granted shortly beforehand based on the stock price reaction to patent approval. The two sets of patents are comparable because they were both filed pre-intervention due to the long and semi-random delay between filing and granting of about two to three years. We document a significant increase of 31 to 45 basis points in abnormal stock return around the patent grant day if the latter occurs post-intervention, suggesting the pre-existing innovation outputs become more valuable because they are better utilized and allocated under the "new" regime.

Our study presents a nuanced picture about whether hedge fund activism or pressure from the stock market in general encourages or impedes corporate innovation. Our overall evidence suggests that firms become "leaner" but not "weaker" subsequent to hedge fund interventions. Moreover, the efficiency gains also emanate from the extensive margin through the redeployment of innovative assets (patents or innovators). This pattern parallels activist hedge funds' role in improving the productivity of physical assets through reallocation (i.e., plant sales and other strategic changes in the allocation of firm resources), as documented by Brav et al., (2015b). Activists are effectively

[6] A shareholder who acquires more than 5% beneficial ownership is required to disclose the holdings in the SEC Schedule 13D form within ten days of crossing 5% if it intends to influence control. If the investment intention is purely passive, the disclosure requirement is a less stringent 13G form. Section 5 provides a more detailed discussion of these filing requirements. Several recent studies have applied this identification scheme in similar settings, including Brav, Jiang, and Kim (2015b) and Aslan and Kumar (2016).

redrawing the target firm's boundaries via the refocusing and leveraging of core competency.

Our study contributes to the growing literature exploring how financial markets and corporate governance affect corporate innovation, where earlier studies examined the effects from firms' public offering decisions (Bernstein, 2015), anti-takeover provisions (Atanassov, 2013), and institutional ownership (Aghion et al., 2013). We relate innovation to an increasingly important new form of market-based corporate governance, hedge fund activism, to inform the current debate as to whether the pressure from empowered shareholders impacts the long-term viability of public companies. Closest to our paper is Seru (2014), who argues that firm boundaries matter for innovation by showing that firms acquired in diversifying mergers produce fewer and less novel patents afterwards and that this is driven by a decline in inventors' productivity rather than inventor exits. Our study illustrates in a different setting how the redrawing of firm boundaries, by the activists rather than via a change in control, leads to higher innovative efficiency. Our paper is also related to recent work on the effect of private equity involvement with innovation (Lerner et al., 2011). Activist hedge funds are, however, critically different from private equity in that their primary role is not financing, but rather to act as vigilant external monitors without taking control. For this reason, activist hedge funds do not target fledging enterprises that need nurturing; instead they seek more mature firms that are prone to the agency problems of free cash flows described in Jensen (1986). We therefore view the two bodies of work as complementary in studying innovation in different stages of the firms' life cycle.

2. Data and sample overview

2.1. Data sources

2.1.1. Innovation

Two sets of measures capture the input to and the output from the innovation process in our study. The input measure is the level of annual R&D expenditures from Compustat. While simple and intuitive, this measure suffers from several limitations: It is incomplete with more than 50% of the observations missing in Compustat; it captures only one particular observable and quantifiable input; and it is sensitive to accounting discretion regarding whether it should be capitalized or expensed (Acharya and Subramanian, 2009).[7]

The second set of measures, capturing the output from the innovation process, is a firm's patenting activity, reflecting a standard practice in the literature (e.g., Acharya and Subramanian, 2009; Aghion et al., 2013; and Seru, 2014).[8] We access the National Bureau of Economic Research (NBER) patent database as of 2013 to obtain annual patent-level information from 1991 to 2006. The relevant variables include information on the patent assignee (the entity, such as the firm, which owns the patent), the number of citations received by the patent, the technology class of the patent, and the patent's application and grant year. Bhaven Sampat's United States Patent and Trademark Office (USPTO) patent and citation database allows us to extend the NBER patent database up to 2010.[9]

In addition to general patenting activities, we are further interested in measuring the reallocation of both patents and human capital subsequent to the arrival of hedge fund activists. We track inventor mobility using the Harvard Business School (HBS) patent and inventor database.[10] Covering the period from 1991 to 2010, this database provides the names of the inventors (the individuals who receive credit for producing a patent) and their affiliations with the assignees, thus enabling us to track their mobility (see Lai et al., (2014) for details).

We create a database of patent transactions based on the USPTO patent assignment files, hosted by Google Patents.[11] The data include the following information: 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. We merge the raw assignment data with the USPTO patent database so as to gather additional information on the original assignees and patent technology classes, and with the HBS inventor database. Following Serrano (2010), Akcigit et al., (2016), and Ma (2017), we then identify patent transactions from all patent reassignment records.[12]

2.1.2. Hedge fund activism

The sample of hedge fund activism events, covering the period from 1994—2007, is an extension of the sample studied in Brav et al., (2008), which describes the details of the sample selection criteria. The events are identified mainly through Schedule 13D filings submitted to the Securities and Exchange Commission (SEC) (accessible via the EDGAR system). These filings are required for any investor who owns more than 5% of any class of publicly traded securities of a company and who intends to influence corporate policy or control. We then supplement this sample using news searches for activists who own between 2% and 5% of shares at mid- to large-cap companies (companies with more than $1 billion in market capitalization).

Panel A of Table 1 reports the number of hedge fund activism events for each year from 1994 to 2007. The number of events increased over our sample period, but with some evidence of pro-cyclicality. Given the goals of this study, we limit the sample to potentially "innovative firms," de-

[7] Following the norm in the existing literature, we impute missing values of R&D as zero if the same firm reports R&D expenditures for at least one other year during the sample period. Otherwise, we treat the observation as missing.

[8] Although there have long been criticisms of the patenting measure under certain circumstances, including defensive patenting, patent thickets, and potential abuses by patent trolls (e.g., Shapiro, 2001; Bessen, Ford, and Meurer, 2011), the consensus in the literature appears to be that it remains a reasonable proxy for innovation.

[9] Available at: http://thedata.harvard.edu/dvn/dv/boffindata.

[10] Available at: http://dvn.iq.harvard.edu/dvn/dv/patent.

[11] The data are accessible via bulk downloading of text files. See http://www.google.com/googlebooks/uspto-patents.html.

[12] We do not include reassignments associated with cases involving a patent transfer from an inventor to her employer or transfers between two subsidiaries of a firm. Online Appendix 3 provides a more detailed description of the data and methodology.

Table 1
Hedge fund activism and innovation by year and industry.
This table provides descriptive statistics on hedge fund activism events by year (Panel A) and by industry (Panel B). We identify hedge fund activism events through Schedule 13D filings, which are mandatory SEC disclosures of share ownership exceeding 5% with an intention to influence corporate policy or control. We supplement these filings with news searches for events in which activists hold ownership stakes between 2% and 5% at companies with $1 billion or more in market capitalization. A target firm is broadly defined as an “innovative target” if the firm filed at least one patent in any year prior to the activism event with at least one positive R&D expenditure within the five-year window prior to the intervention. We also report on an alternative and narrower measure for an “innovative target,” requiring that the firm file at least one patent between three years and one year prior to the activism event with at least one positive R&D expenditure within the five-year window prior to the intervention. Panel A reports the annual number of hedge fund activism events between 1994 and 2007, the proportion of innovative firms targeted in each year, and the median number of patents owned by those target firms in the event year. Panel B reports the number of hedge fund activism events and the proportion of innovative targets across the Fama-French 12 industries.

Panel A: Hedge fund activism by year

		Innovative targets: Firms that filed a patent in any year prior to year t		Innovative targets: Firms that filed a patent from year $t-3$ to year $t-1$	
Year	(1) # of Events	(2) % of Innovative targets	(3) # of patents owned by targets (median)	(4) % of Innovative targets	(5) # of patents owned by targets (median)
1994	8	37.50	138	37.50	138
1995	28	46.43	2	35.71	2
1996	82	36.59	12	30.49	15
1997	178	22.47	11	19.10	12.5
1998	140	30.71	12	25.00	18
1999	99	20.20	18	16.16	26
2000	98	21.43	19	19.39	19
2001	85	29.41	18	24.71	20
2002	119	32.77	10	27.73	13.5
2003	112	36.61	14	29.46	17
2004	133	34.59	7	27.82	10
2005	203	30.05	13	22.17	20
2006	235	34.47	24	24.26	50
2007	250	36.00	21	23.20	36
Full sample	1,770	31.24	16	24.07	24

Panel B: Hedge fund activism by industry

	# of Events	% of Innovative targets: Firms that filed a patent in any year prior to year t	% of the Industry in the whole sample of innovative targets	% of Innovative targets: Firms that filed a patent from year $t-3$ to year $t-1$	% of the Industry in the whole sample of innovative targets
Consumer Nondurables	94	36.17	6.15	21.28	4.70
Consumer Durables	47	61.70	5.24	59.57	6.57
Manufacturing	166	59.04	17.72	46.39	18.08
Energy	64	9.38	1.09	3.13	0.47
Chemicals and Allied Products	33	60.61	3.62	48.48	3.76
High Tech	346	51.45	32.19	41.04	33.33
Tele and Communications	73	12.33	1.63	9.59	1.64
Utilities	29	6.90	0.36	3.45	0.23
Wholesale and Retail	225	9.33	3.80	5.78	3.05
Healthcare, Medical Equipment, and Drug	192	53.13	18.45	46.35	20.89
Finance	238	5.04	2.17	2.10	1.17
Others	263	15.97	7.60	9.89	6.11
Full sample	1,770	31.24	100	24.07	100

fined in two ways. The first definition requires that the firm filed at least one patent in any year prior to hedge fund intervention and with at least one positive R&D expenditure within the five-year window prior to the intervention. The second definition narrows the time window and requires that the firm filed at least one patent in the three-year period prior to hedge fund intervention (i.e., $t-3$ to $t-1$) and the same criterion for R&D. Table 1 Panel A indicates that about 31% of the hedge fund targets are innovative firms according to the first definition (columns 2 and 3) and 24% are innovative firms based on the more stringent second definition (columns 4 and 5). On average, innovative target firms own about 20 patents in the year of the hedge fund intervention. Panel B of Table 1 shows the number of hedge fund activism events and the representation of innovative firms for each of the Fama-French 12 industries.[13] Naturally, the sample is most over-represented in the high tech (32% of the sample), healthcare (18% of the sample), and manufacturing (18% of the sample) industries.

[13] Detailed industry definitions can be downloaded from Ken French's Data Library at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

2.2. Main innovation variables

2.2.1. Patent quantity and quality

Patents are the most natural and measurable output from the process of innovation. Patent quantity can be measured as the number of patent applications filed by a firm in a given year that are eventually granted. Moreover, the application (rather than grant) year better captures the actual time of innovation (Griliches et al., 1987).

There are several frequently used measures for patent quality, including the number of subsequent lifetime citations, the patent's originality, and the patent's generality. The first measure, the number of citations that each patent receives in subsequent years, emphasizes impact. The literature has also developed two mitigating solutions to two truncation problems associated with this measure. The first problem arises because patents appear in the database only after they are granted, and there is a significant lag (about two years, on average) between the application and the eventual grant date. As a result, patent applications filed toward the end of our sample period are underrepresented. Hall, Jaffe, and Trajtenberg's (2001, 2005) "weight factors" have become the standard procedure to adjust the empirical distribution of granted patents. The second problem arises because of sample-end censoring (in our study, the sample ends in 2010). The same references suggest that we correct the bias by dividing the observed citation counts by the fraction of predicted lifetime citations based on a citation-lag distribution. The resulting adjusted patent counts and citations are both right skewed, justifying the log-transformation of the variables in the regressions.

It is worth noting that firm attrition from our sample does not compromise the NBER Patent and Citation database since information is recorded at the patent level. As long as a patent is eventually granted it is properly attributed to the assignee at the time of application even if the firm has since been acquired or filed for bankruptcy, and citations are properly accrued to the patent.

Second, Hall, Jaffe, and Trajtenberg (2001) develop two measures of the quality and importance of patents beyond a simple citation count. Patents that cite a wider array of technology classes of patents are viewed as having greater originality, while patents that are cited by a wider array of patent technology classes are viewed as having greater generality. More specifically, a patent's originality score is one minus the Herfindahl Index of the three-digit technology class distribution of all the patents it cites. A patent's generality score is one minus the Herfindahl Index of the three-digit technology class distribution of all the patents that cite it. We follow Kerr and Nanda's (2015) recommendation for the reporting of originality and generality by tracing these metrics' evolution in the years prior and subsequent to the arrival of activists.

Last, we follow Kogan et al., (2017) in measuring the quality of innovation using the market value of a new patent as implied by the market responses to the patent approval. A patent's value is measured as the target firm stock return in excess of the market over the three-day window around the date of patent approval, multiplied by the firm's market capitalization on the day prior to the announcement.

2.2.2. Innovation strategy

Turning from patents to firms, we employ three variables to describe a firm's innovation strategy. The first variable, proposed by Sorensen and Stuart (2000) and further extended by Custódio et al., (2018), measures a firm's innovation diversity. This diversity measure equals one minus the Herfindahl Index of the number of new patents across different technological classes, measured over the most recent three years. A high diversity value indicates higher diversification, or lower concentration of patenting activities, across different technology classes.

The second variable, proposed by Manso (2011) and further extended by Almeida et al., (2013) and Custódio et al., (2018), summarizes the innovation strategy as the extent to which the new patents are exploratory or exploitative. A patent is considered exploitative if at least 80% of its citations are based on the existing knowledge of the firm, whereas a patent is exploratory if at least 80% of its citations are based on new knowledge. Existing knowledge includes all the patents that the firm invented and all the patents that were cited by the firm's patents filed over the past five years. The two categories are not exhaustive. Aggregated at the firm-year level, the percentage of exploitative/exploratory new patents is indicative of whether a firm's innovative strategy relies heavily on existing knowledge (e.g., incremental advances relative to existing patents) or focuses on exploring new technologies.

The last variable is the distance between a given patent and the firm's overall patent portfolio. Following Akcigit et al., (2016), we first calculate the distance between any two technology classes as the ratio of the number of all patents that simultaneously cite patents from both technology classes to the number of all patents that cite at least one patent from either of these technology classes, or both. Next, we measure a patent's distance from the firm's overall patent portfolio as the weighted average of the patent's distance to each of the other patents that a firm owns using these technology class distance measures. The caption to Table 5 provides the precise derivation of this measure.

At a more general level, Lerner and Seru (2017) suggest that researchers confirm that their analyses are robust to several potential biases, which may arise from the use of the patent data. They propose a checklist comprised of several questions that we present in Appendix B along with our responses to these questions.

2.3. Sample overview

We merge all the databases described in the previous sections to form the master database. Our main analyses are conducted on the pooled sample of hedge fund target firms and firms matched by propensity scores. We match each firm targeted by a hedge fund in year t with a non-target firm from the same year and 2-digit Standard Industrial Classification (SIC) industry code that has the closest propensity score, estimated using variables identified by the existent literature as the most effective predictors, including log firm size, market-to-book ratio, return on assets (ROA) measured at $t-1$, and the change in the target firm ROA measured between years $t-3$ and $t-1$ to capture

Table 2
Summary statistics for the target firms and the matched control sample.
This table reports firm characteristics at the firm-year level for the subsample of innovative target firms defined as firms that filed for at least one patent that was eventually granted prior to the year of the hedge fund intervention with at least one positive R&D expenditure within the five-year window prior to the intervention and for the control sample. 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, market-to-book ratio, return on assets (ROA) measured at $t-1$, and the change in the target firm ROA measured between years $t-3$ and $t-1$. The variable values are measured as of the year prior to the hedge fund intervention. For each variable, we report the mean, standard deviation, 25th, 50th, and 75th percentiles. We also report the t-statistics for the differences in mean values between the targets and matched firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

	Targets ($N=553$)					Non-targets ($N=553$)					Difference	
	Mean	S.D.	p25	p50	p75	Mean	S.D.	p25	p50	p75	Target–Non-targets	t-Statistic
Ln(Firm assets)	5.48	1.61	4.21	5.47	6.74	5.41	1.64	4.25	5.36	6.68	0.08	(0.76)
Ln(MV)	5.42	1.59	4.17	5.41	6.73	5.51	1.54	4.44	5.55	6.74	−0.09	(−0.88)
Firm assets	721.54	1049.17	67.30	237.49	849.32	704.06	1059.63	70.07	212.78	792.90	17.48	(0.27)
MV	631.88	862.10	63.29	222.16	814.13	627.49	848.92	80.15	234.42	807.43	4.39	(0.08)
Firm ROA	0.01	0.15	−0.06	0.05	0.11	0.02	0.16	−0.05	0.07	0.13	−0.01	(−0.88)
Firm R&D/Assets	0.07	0.08	0.00	0.03	0.13	0.07	0.07	0.00	0.04	0.11	0.00	(0.77)
Leverage	0.20	0.20	0.01	0.16	0.31	0.17	0.18	0.01	0.12	0.28	0.03*	(2.28)
Firm market-to-book ratio	1.52	0.97	0.84	1.23	1.83	1.60	0.98	0.88	1.28	2.05	−0.08	(−1.39)
Ln(1 + New patents)	0.50	0.72	0.00	0.00	1.10	0.53	0.74	0.00	0.00	1.10	−0.02	(−0.49)
Ln(1 + Ave.citation)	0.55	0.98	0.00	0.00	0.00	0.55	0.98	0.00	0.00	0.53	0.00	(−0.03)
Number of new patents	1.27	2.11	0.00	0.00	2.00	1.37	2.22	0.00	0.00	2.00	−0.10	(−0.73)
Ave. citation of new patents	2.22	4.27	0.00	0.00	0.00	2.20	4.19	0.00	0.00	0.70	0.02	(0.09)
Firm patent originality	0.58	0.24	0.48	0.63	0.76	0.59	0.24	0.44	0.63	0.78	−0.01	(−0.26)
Firm patent generality	0.53	0.27	0.33	0.57	0.70	0.54	0.29	0.35	0.60	0.73	−0.01	(−0.35)
Firm patenting explorative	0.18	0.34	0.00	0.00	0.20	0.19	0.34	0.00	0.00	0.33	−0.01	(−0.38)
Firm patenting exploitative	0.29	0.42	0.00	0.00	0.75	0.29	0.42	0.00	0.00	0.75	−0.01	(−0.22)

pre-event trends of deterioration in the operating performance of target firms.

Table 2 reports summary statistics (at the year before the event) comparing the characteristics of the hedge fund target firms with those of the matched firms. All potentially unbounded variables are winsorized at the 1% extremes. As discussed in Section 2.1.2, the focus of this study centers on innovative firms, that is, firms filing at least one patent in any year (or, depending on the definition of an innovative firm, within three years) prior to the event year. Table 2 presents the mean, standard deviation, 25th, 50th, and 75th percentile for each of the firm characteristics. The last two columns report the differences and the t-statistics testing the equality of means of the two samples. The target and matched firms are indistinguishable along multiple characteristics, such as size, market-to-book ratio, and ROA, although hedge fund targets have marginally higher leverage.

Importantly, the two samples are similar in both innovation inputs and outputs in the year of intervention, despite the fact that these characteristics are not part of the matching criteria, supporting the assumption of a "parallel trend." For example, both invest an equivalent of 7% of their total assets in R&D during the event year. Target firms (control firms) file 1.27 (1.37) patents in the event year, and each patent receives a total of 2.22 (2.20) citations in all future years. None of the differences in the other innovation quality measures are significant either economically or statistically.

3. Corporate innovation prior to and post hedge fund activism

Our empirical analyses begin with an examination of the relationship between hedge fund activism and corporate innovation. The sample consists of firm-year level observations from 1991 to 2010, in which firms are limited to hedge fund targets and their matched firms. The event year for a target firm also serves as the "pseudo-event" year for its matched firm. The sample is further restricted to observations beginning five years prior to the event year (pseudo-event year) through five years afterwards.

We adopt the following standard difference-in-differences (DiD) regression framework:

$$Innovation_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(Target_i) \times I(Post_{i,t}) + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t} \quad (1)$$

In Eq. (1), i and t are subscripts for firm and year, respectively. The dependent variable $Innovation_{i,t}$ is equal to one of the innovation input/output proxies described in Section 2. $I(Target_i)$ is a dummy variable equal to one if firm i is the target of hedge fund activism. $I(Post_{i,t})$ is a dummy variable equal to one if the firm-year (i,t) observation is within $[t+1,\ t+5]$ years of an activism event (for target firms) or a pseudo-event year (for match firms). The results are robust if we instead use the three-year period following the event. Finally, α_t and α_i represent year and firm fixed effects, respectively, and $Control_{i,t}$ is a vector of control variables, including market capitalization and firm age (both in logarithmic terms). The coefficient of key interest is thus β_1, associated with the interaction term $I(Target_i) \times I(Post_{i,t})$, which indicates the differential change in innovation inputs/outputs in target firms post hedge fund intervention, compared to those for matched firms. Table 3 reports the results of regression (1).

Columns 1 and 2 of Table 3, Panel A provide results in which we use two measures of inputs to innovation. The first dependent variable is the annual R&D expenditures scaled by firm assets, measured in percentage points, and the second is the level of annual R&D expenditures,

Table 3
Innovation subsequent to hedge fund activism.
This table documents the dynamics of inputs to and outputs from innovation around hedge fund interventions. We use the following difference-in-differences specification:

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

The sample includes hedge fund targets and non-targeted control firms, as described in Table 2. We include observations from five years prior to through five years post-intervention for both the targets and the 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). Panel A examines the inputs and outputs of innovation. 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 A. 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., (2017). Panel B examines specific subsamples. Column 1 constrains the sample to new patents that are in the top 20% most cited firms, at the firm-year level. Columns 2 and 3 focus on the chemical, healthcare, medical equipment, and drug (CHMD) industries which tend to have long lags between R&D and new patents. Columns 4 and 5 analyze the complement set of non-CHMD industries. 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.

Panel A: Innovation inputs and outputs

	(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)	−0.151	−11.007***	0.151***	0.155***	0.027***	0.009	12.260*
	(−1.323)	(−3.086)	(3.711)	(3.071)	(2.816)	(1.109)	(1.784)
I(Post)	0.061	4.648	−0.060*	0.007	−0.049***	−0.003	−4.593
	(0.430)	(1.044)	(−1.935)	(0.176)	(−3.973)	(−0.279)	(−0.584)
ln(MV)	−0.580***	5.361***	0.047***	0.048***	0.012***	0.009***	−0.435
	(−13.736)	(4.058)	(4.076)	(3.310)	(3.476)	(2.963)	(−0.151)
ln(Age)	0.014	−2.713	−0.029	−0.084	−0.022*	0.008	17.670**
	(0.108)	(−0.677)	(−0.747)	(−1.506)	(−1.888)	(0.715)	(2.524)
Observations	9,817	9,817	9,817	9,817	3,218	2,763	3,218
R-squared	0.888	0.909	0.632	0.555	0.506	0.460	0.625
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Subsample evidence

		Chemical, Healthcare, Med Equip, & Drug (CHMD)		Non-CHMD	
	(1) Quality of top 20% most-cited patents	(2) Log(1 + # New patents)	(3) Log(1 + Ave.citations)	(4) Log(1 + # New patents)	(5) Log(1 + Ave.citations)
I(Target) × I(Post)	0.172**	0.231***	0.143	0.129***	0.171***
	(2.250)	(2.919)	(1.458)	(2.748)	(2.960)
I(Post)	−0.100	−0.077	0.009	−0.053	−0.007
	(−1.462)	(−1.201)	(0.119)	(−1.492)	(−0.150)
ln(MV)	0.096***	0.061***	0.034	0.043***	0.054***
	(3.683)	(2.899)	(1.093)	(3.204)	(3.229)
ln(Age)	−0.281***	−0.023	−0.059	−0.027	−0.076
	(−3.805)	(−0.323)	(−0.550)	(−0.587)	(−1.155)
Observations	9,817	2,138	2,138	7,679	7,679
R-squared	0.576	0.660	0.586	0.626	0.551
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

measured in millions of dollars. The coefficients associated with $I(Target_i) I \times I(Post_{i,\ t})$ are both negative, but only significant in the second specification, and show that, on average, target firms' total R&D expenditures decrease by $11 million post-intervention (about 20% of the average R&D in our sample), relative to the changes incurred by matched firms during the same time period. Panel A of Fig. 1 further confirms that there is clearly no pre-trend, nor post-event deviation, in the *R&D/Assets ratio*. The finding that R&D expenditures decrease significantly while the *R&D/Assets ratio* remains flat is consistent with the fact that, post-activism, R&D expenditures scale back roughly in proportion to the reduction in the target firms' assets due to both a drop in capital expenditures and an increasing rate of asset spinoffs/sales (Brav et al., 2015a).

Column 3 examines the number of new patents. The dependent variable is the logarithm of new patents plus one. Hence, the estimated coefficients should be interpreted in semi-elasticity terms. Subsequent to the arrival of hedge fund activists, target firms file for about 15.1% more patent applications, compared to the matched firms, controlling for both firm and time fixed effects. The effect is

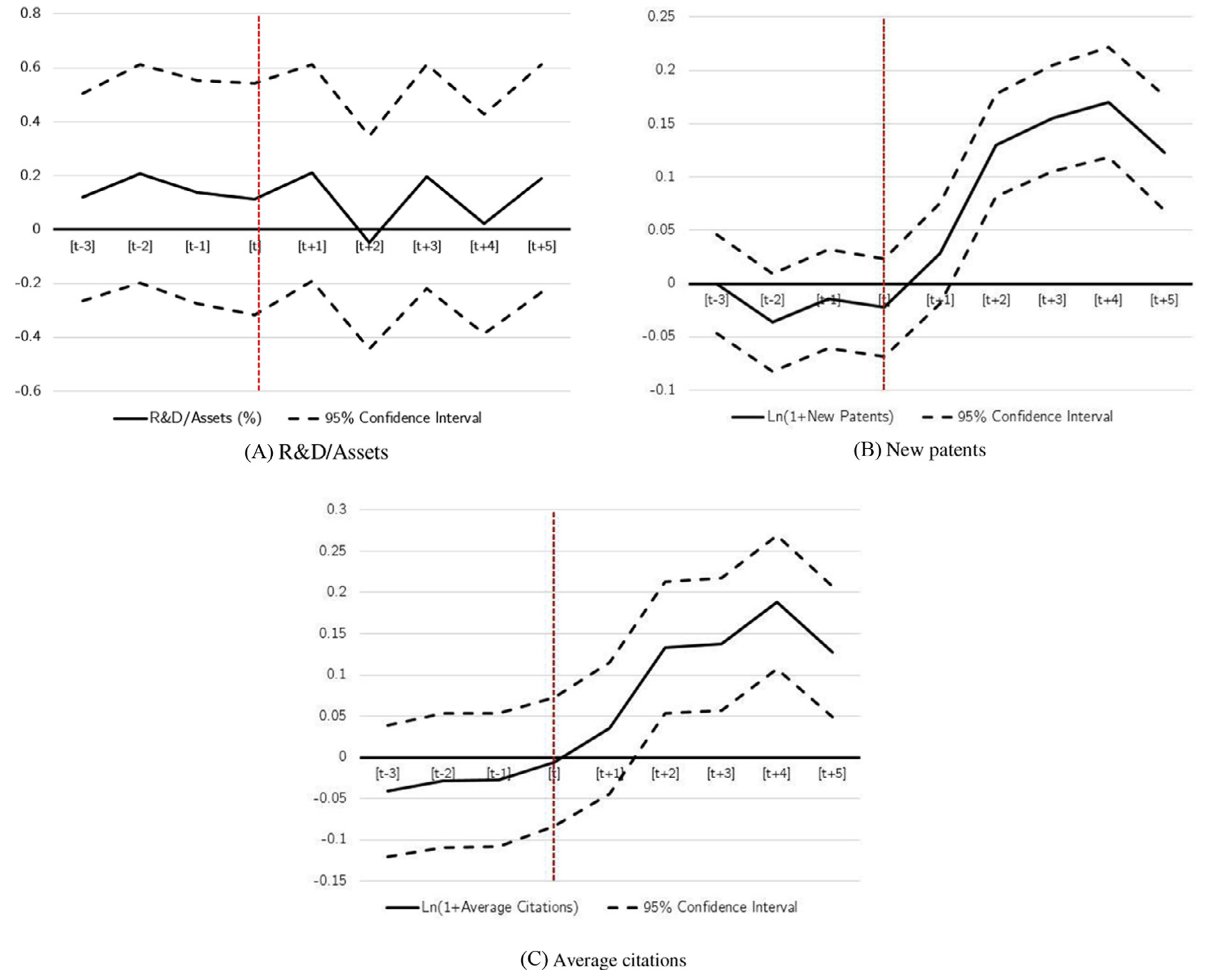


Fig. 1. Innovation around hedge fund activism. This figure presents the dynamics in innovation, as measured by R&D expenditures scaled by total assets, the number of patent applications, and their subsequent lifetime citations, in the years around the targeting by hedge fund activists. We employ the sample of innovative hedge fund targets and propensity-score-matched firms, retaining only those target firms that file for a patent at least once prior to the event with at least one positive R&D expenditure within the five-year window prior to the intervention. The unit of observation is at the firm (i)-year (t) level. The coefficients and 95% confidence intervals are estimated from the following specification:

$$Innovation_{i,t} = \sum_{k=-3}^{+5} \lambda_k \, d[t+k]_{i,t} + \sum_{k=-3}^{+5} \beta_k \left\{ d[t+k]_{i,t} \times I(Target_i) \right\} + \gamma \cdot Control_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

The dummy variable *d[t + k]* is equal to one if the firm observation is k years from the hedge fund activism event year (pseudo-event year for the control firms), and zero otherwise. We plot the β_k coefficients, which are the estimates representing the differences in trends in innovation between hedge fund targets and the matched control firms. The dependent variable in Panel A is R&D dollars scaled by total assets, that in Panel B is the logarithm of the number of patents filed by firm i in year t, and that in Panel C is the logarithm of the average lifetime citations received by patents filed by the firm in year t. Control variables include the natural logarithm of firm market capitalization and firm age. All specifications include firm and year fixed effects. Standard errors are clustered at the firm level.

statistically significant and economically sizable, especially when considering that the mean of the dependent variable ln*(number of new patents*+1*)* is 0.50 (see Table 2). Needless to say, the quality of patents is as important as the quantity. The remaining four columns in Panel A provide evidence on changes in patent quality using several commonly used proxies for quality.

In Column 4, the dependent variable is the logarithm of the average number of citations per patent plus one. The coefficient on $I(Target_i) \times I(Post_{i,\,t})$ is statistically significant, indicating that patents filed post-intervention collect 15.5% more citations, on average, than patents filed by matched firms during the same period.[14] Columns 5 and 6 show that the originality and generality scores of

[14] There has been an increasing concern that some investors attempt to profit from patents via aggressive litigation rather than by a productive use. To examine this possibility, we obtain litigation data from Lex Machina, Derwent LitAlert, and the RPX database, and apply the same difference-in-difference regression framework as in Table 3, except that we replace the dependent variable to be the number of patent litigation cases initiated by a firm in a given year. The Online Appendix Table A1 shows that the coefficient on $I(Target_i) \times I(Post_{i,\,t})$ is economically small and indistinguishable from zero, suggesting that activism does not lead to more aggressive litigation related to IP infringement.

patents filed by target firms post-event also increase relative to matched firms, although only the coefficient estimate associated with originality is significant. Finally, Column 7 provides evidence on changes in patent quality post-activism, as measured by the market value of new patents implied by market responses to patent approvals (defined in Section 2.2.1). The dependent variable, *Yearly innovation value*, aggregates the sum of stock market reactions to all patents applied for in a given year. On average, target firms see an increase of $12 million in their market capitalization relative to the matched controls in the post-intervention period, marginally significant at the 10% level.

Panel B explores specific subsamples that are particularly informative about the nature of the improvement. Column 1 constrains the previous analysis on citations for new patents to the subset of new patents that rank in the top 20% most cited patents produced by firm i in year t in order to assess the impact of intervention on the presumably most valuable innovative assets. The positive and significant slope on the interaction term indicates that the shift in quality documented in Panel A encompasses the top end of the quality spectrum.

Next, we examine whether the main results hold in industries with short lags between the inputs (e.g., R&D and strategic planning) and the realization of innovation (e.g., patents). Evidence for an improvement in patenting activities in industries with short lags would serve to alleviate the concern that hedge funds select firms with more patents in the pipeline prior to the intervention. To calibrate the length of the time lag, we follow Hall et al., (1986) and regress, for each industry, the number of new patents on R&D expenditures in the current and each of the past five years at the firm-year level. Confirming the earlier study, we find that only the following four industries have coefficients that are significant beyond the one-year lag: chemical, healthcare, medical equipment, and drug (CHMD). We thus analyze the number of patents and average citations separately for the CHMD subset and non-CHMD industries.

The results are reported in Panel B, Columns 2 through 5. We find that, subsequent to the arrival of hedge fund activists, target firms in non-CHMD (CHMD) industries file about 12.9% (23.1%) more patent applications than matched firms controlling for both firm and time fixed effects. We also observe that subsequent lifetime citations to these new patents increase for both subsamples, although the increase is significant only for the non-CHMD industries. The improvement in innovation at non-CHMD industries coupled with the evidence, presented later in this section, that the increase in target firms' innovation is significant beginning only in the second year after the arrival of activists, help to mitigate the concern that the results reported in Panel A of Table 3 are driven by activists' ability to select target firms that are about to file for new patents. We revisit the issue of selection and causality more formally in Section 5.

Confirming that the results are not driven by different pre-event trends between targets and their matched controls, Fig. 1 displays the changes in the input and output from innovation at target firms relative to that of control firms by plotting the differences in pre- and post-trends in *R&D/Assets*, the number of new patents, and associated citations between targets and controls. The coefficients, $\beta_{-3}, \ldots, \beta_5$, are the slopes on the interactions of yearly dummies extending from three years prior to the activism event year (or pseudo-event year) through five years afterwards and an indicator of being targeted by hedge funds. The coefficients are estimated from the following specification in Eq. (2):

$$Innovation_{i,t} = \sum_{k=-3}^{+5} \lambda_k \, d[t+k]_{i,t} + \sum_{k=-3}^{+5} \beta_k \left\{ d[t+k]_{i,t} \times I(Target_i) \right\} + \gamma \cdot Control_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}. \quad (2)$$

As in Eq. (1), the control variables include the natural logarithms of firm market capitalization and firm age. We also include firm and year fixed effects. Panel A plots the estimates of the difference between targets and controls in *R&D/Assets*. Panel B plots the estimates of the difference between target and control firms in the quantity of innovation, as measured by the logarithm of the number of patents filed by firm i in year t. Panel C plots the estimates of the difference between target and control firms in the quality of innovation, as measured by the logarithm of the average citations received by patents filed by the firm in year t.

Fig. 1 shows that differences between target and control firms in all three variables are negligible during the three years prior to the arrival of activist hedge funds. The parallel trend in the R&D input continues into the post-intervention years, but divergence emerges within one to two years for the output measures, and the departure in the number of patents (citations per patent) is statistically significant in the second year post-intervention. Combining the evidence on both inputs and outputs, Table 3 and Fig. 1 suggest that target firms become more efficient in the process of innovation.

The positive impact on innovation offers one explanation for the widely documented positive stock market response to the announcement of hedge fund activism, with no evidence of a reversal in the longer run.[15] The length of time it takes for external shareholder monitoring to manifest in the change in innovation activities that we document is also plausible. It is similar to that reported in Lerner et al., (2011) for private equity firms, and is consistent with the holding horizon of the activists. Table A3 in the Online Appendix shows that the average holding period for activists in innovative firms in our sample is about two and a half years (982 days), and the median is 717 days. Committing to own the target for this long affords the time needed to bring the innovation strategies onto a

[15] The [-20,+20] day window stock abnormal return for our innovative firm sample is around 6%, comparable to the short-term stock market reaction in the full sample of activist targets. The abnormal return does not revert during the five-year period post-intervention. See Table A2 in the Online Appendix for the detailed calendar-time portfolio regression evidence.

new path and to see the innovative effort to at least some form of fruition.[16]

The Online Appendix provides several additional analyses and robustness checks. First, given the importance of the propensity score matching in our analysis, we conduct several diagnostic and robustness checks in the Online Appendix. We confirm that the distribution of the propensity scores are similar among treated and control firms and show in Table A5 that our results remain qualitatively unchanged when using only observations that fall in the region of common support, defined as the intersection of the support of the treated and control propensity scores. Table A6 shows that our results are robust when we implement the matching algorithm with replacement and Table A7 provides alternative specifications of the propensity score matching meant to capture the pre-event change in performance of target firms.

Second, we examine whether the innovative outcomes exhibit heterogeneity over whether hedge funds' stated objectives include business strategies. Table A8 reveals that improvements in innovation outputs are significant in both subsamples with comparable magnitude.[17] Third, we restrict the definition of "innovative" target firms to those that have at least five patents prior to the year of the intervention and Table A9 shows qualitatively similar evidence regarding the decrease in R&D expenditures ($15.6 million), increase (16% more) in patent applications, and improved per-patent citations (15.5% more). Fourth, Table A10 adopts a negative binomial specification instead of that in Eq. (1), including year and firm fixed effects, and we find a similar strong positive estimate on the interaction term $I(Target_i) \times I(Post_{i,t})$. Fifth, we show in Table A11 that our results are qualitatively unchanged during the subperiod through 2002 for which censoring is not an issue (Dass et al., 2017) and are not sensitive to the exclusion of the seemingly unusual year of 1994 (Table A12). Sixth, we show that our results are robust to the use of industry-by-year fixed effects (Table A13) and for an alternative control for firm size in the post-event period using size measured as of the year prior to the event (Table A14), thus mitigating the concern that market value could itself be affected by the treatment.

Finally, Table A15 in the Online Appendix addresses the potential effect from firm attrition in our sample during the post-intervention years. We first confirm a finding in the prior literature (e.g., Greenwood and Schor, 2009; Brav et al., 2015a; and Boyson et al., 2017) that non-innovative targets of activism experience a higher rate of attrition from Compustat, especially due to acquisitions. More interestingly, we find that innovative targets are no more likely than their propensity-score-matched control firms to experience attrition or to be acquired. Moreover, the probability that innovative targets are delisted due to distress reasons (including bankruptcy) post-intervention is actually over 20% lower compared to the matched firms. Thus, activism targeting innovative firms seems to be more long-term focused and operation-oriented rather than acquisition-driven. Such a finding also differentiates our study from those on hedge fund activism without a focus on innovation.

4. Hedge fund activism and innovation: potential channels

The challenge to identify the channels through which activism improves innovation efficiency is that most activist shareholders are not perceived to be experts in the target firms' technological domain and activist proposals do not commonly state as a goal the reformulation of the target firm's innovation (in either the Schedule 13D filing or in accompanying news releases). The main contribution of this study is thus to enhance our understanding of the possible channels to support a likely causal impact of hedge fund activists.

4.1. Refocusing of innovation

Several recent studies have analyzed the effect of diversity on innovation, following the literature on the scope of operations and the value of the firm (see the survey by Stein (2003)). For example, Seru (2014) shows that although target firms in diversifying mergers produce fewer and less novel patents after such mergers, firms overcome this reduction by increasing innovation outside the firm's core expertise using strategic alliances and joint ventures. In a related setting, Bena and Li (2014) show that firms are more likely to acquire technologically similar targets and synergies in these types of mergers are associated with larger benefits.

Our test is motivated by Akcigit et al., (2016), who show that a patent contributes more to a firm's value if the patent is closer to the firm's technological expertise and core business area. The body of literature on hedge fund activism, reviewed in Brav et al., (2015a), provides a coherent pattern: Hedge fund activists tend to make their targets leaner and more focused by trimming off unproductive and peripheral assets, unbundling business segments, and opposing diversifying acquisitions. Therefore, we expect that firms with a more diverse portfolio of innovation at the outset will benefit more from the strategic changes brought about by activists. An empirical assessment of such cross-sectional heterogeneity requires that we re-run Eq. (1) with the addition of two interaction terms, $I(HighDiv_i)$ and $I(LowDiv_i)$, which are disjoint dummy variables indicating whether a firm's patent diversity during the event (or pseudo-event) year is above or below the median. That is, the regression specification is now:

$$\begin{aligned} Innovation_{i,t} = {} & I(HighDiv_i) \cdot [\beta_1 \cdot I(Target_i) \times I(Post_{i,t}) \\ & + \beta_2 \cdot I(Post_{i,t})] + I(LowDiv_i) \\ & \cdot [\beta_3 \cdot I(Target_i) \times I(Post_{i,t}) + \beta_4 \cdot I(Post_{i,t})] \\ & + \gamma \cdot Control_{i,t} + \alpha_t + \alpha_i + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

[16] Innovation outcomes are qualitatively similar when we sort events into terciles by the length of the holding period of activist hedge funds. See the Online Appendix, Table A4.

[17] The fact that stated objectives (usually captured by the language used in Item 4 of Schedule 13D filings) do not accurately sort out the actual strategies employed by hedge funds is consistent with findings in earlier studies that common outcomes for activist intervention (e.g., increased payouts, sales of the companies, and CEO turnover) are not confined to the subsample with matched stated objectives.

Table 4

Hedge fund activism, innovation, and the diversity of innovation.

The sample consists of the hedge fund targets and matched firms as described in Table 2. In Panel A we use the following specification:

$$y_{i,t} = \alpha_t + \alpha_i + I(HighDiv_i) \cdot [\beta_1 \cdot I(Target_i) \times I(Post_{i,t}) + \beta_2 \cdot I(Post_{i,t})] + I(LowDiv_i) \cdot [\beta_3 \cdot I(Target_i) \times I(Post_{i,t}) + \beta_4 \cdot I(Post_{i,t})] + \gamma \cdot Control_{i,t} + \varepsilon_{i,t}.$$

I(Target) is a dummy variable indicating whether the firm is a target of hedge fund activism, and *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). *I(HighDiv)* and *I(LowDiv)* are dummy variables indicating whether a firm is above or below the median in terms of its patent portfolio diversity (defined in Appendix A), measured at year $t-1$. In Columns 1 and 2 the dependent variable is the natural logarithm of patent counts (plus one). For ease of comparison, the coefficients associated with regressors interacted with *I(HighDiv)*, β_1,and β_2, are reported in Column 1, and those interacted with *I(LowDiv)*, β_3,and β_4, are reported in Column 2. The *F*-test statistic (with *p*-value in parentheses) for the equality of the coefficients associated with *I(Post)* × *I(Target)* is reported in Column 3. In Columns 4 to 6 we perform the same analysis as in the previous three columns except that the dependent variable is replaced by the logarithm of citations per patent (plus one). The control variables include the natural logarithms of firm market capitalization and firm age. In Panel B we focus on the output from innovation in the key technology class of a firm. A technology class is defined as key (non-key) if it includes the largest (smallest) number of patents from the firm's patent stock. We use the following specification:

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

I(Target) and *I(Post)* are as defined above. 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 class 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 that is new (old) to the firm. Appendix A contains the detailed description of these variables. Columns 5 to 8 are analogous to 1 to 4 except that the measures are constructed using innovation in the non-key technology class of the firm. 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.

Panel A: Hedge fund activism, innovation, and diversity of innovation

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(1 + # New patents)			ln(1 + Ave.cit)		
	High diversity	Low diversity	*F*-test	High diversity	Low diversity	*F*-test
I(Target) × I(Post)	0.232***	0.062	5.57**	0.218***	0.092	2.01
	(4.817)	(1.201)	(1.90%)	(3.559)	(1.628)	(15.78%)
I(Post)	−0.077**	−0.042		−0.008	0.018	
	(−2.152)	(−0.828)		(−0.177)	(0.351)	
ln(MV)	0.047***			0.048***		
	(4.772)			(3.733)		
ln(Age)	−0.016			−0.065		
	(−0.464)			(−1.397)		
Observations	9,817			9,817		
R-squared	0.669			0.595		
Year FE	Yes			Yes		
Firm FE	Yes			Yes		

Panel B: Effect on innovation within key and non-key technology classes

	Key technology class				Non-key technology class			
	(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)	0.194***	0.182***	0.040***	−0.045	−0.028	0.027	−0.028	0.016
× I(Post)	(4.469)	(3.444)	(2.671)	(−0.751)	(−0.525)	(0.503)	(−0.401)	(0.267)
I(Post)	−0.055	−0.031	−0.027	0.035	−0.016	−0.032	−0.014	0.031
	(−0.756)	(−0.726)	(−0.829)	(0.603)	(−0.455)	(−0.747)	(−0.241)	(0.555)
ln(MV)	0.053***	0.038**	0.009*	−0.010	0.046***	0.039**	−0.010	−0.006
	(6.011)	(2.344)	(1.943)	(−0.540)	(3.440)	(2.379)	(−0.429)	(−0.321)
ln(Age)	−0.010	−0.114**	−0.022	−0.092**	0.117**	−0.115**	−0.087*	−0.089**
	(−0.211)	(−2.218)	(−1.203)	(−2.060)	(2.199)	(−2.215)	(−1.652)	(−2.022)
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

The two sets of coefficients $\{\beta_1, \beta_2\}$ and $\{\beta_3, \beta_4\}$ are reported in Table 4. Of interest is the test for the equality: $\beta_1 - \beta_3 = 0$, or a triple difference for the differential improvement of firms with diverse versus focused patent portfolios post event.

With regard to the number of new patent applications, Columns 1 and 2 in Panel A present positive estimates of both β_1 and β_3, although only β_1 (for the high diversity subsample) is highly significant, indicating a positive post-intervention effect for the high diversity subsample. Importantly, the estimate of β_1 is 0.232, about four times larger than β_3 (for the low diversity sample), and the *F*-test in Column 3 shows that the difference is statistically significant. The same pattern holds when we look at patent citations (Columns 4 and 5). The difference is positive but insignificant. The message from Panel A is that target firms that had a diverse set of patents prior to the intervention generate more patents and citations per patents within the five-year window after the arrival of activists.

Panel B presents further evidence that the increase in patents and citations is driven by target firms' innovative activities within their core technological expertise by examining the dynamics of output from innovation in key and non-key technology classes. A technology class is key (non-key) to a firm if the highest number (lowest number) of the firm's patent stock is assigned to that class. In Columns 1 and 2, the dependent variables are constructed by counting the number and average citations of new patents in the technology class that is key to a firm. In Columns 5 and 6 the dependent variables are constructed analogously for the firm's non-key technology classes. As seen from the coefficient on the interaction term $I(Target_i) \times I(Post_{i,\ t})$, patent counts and citations increase significantly only in key technology classes (0.194 and 0.182 in Columns 1 and 2). There is no evident increase in either patents or citations in non-key technology classes, as shown in Columns 5 and 6. The Online Appendix Table A16 provides qualitatively similar results when we rank technology classes by the number of the firm's patents assigned to each class and define the top three as key technology classes and the bottom three classes as non-key.

Two questions naturally arise: Do these changes simply reflect added efforts to innovate in the well-trodden areas in which the target had been innovating? Are these genuinely creative attempts to move beyond the past innovations while remaining within the same technological class? To address this set of questions we follow the literature and focus on the intensity of exploration, proxied by the variable *Explorative*, which measures the intensity with which a firm innovates, based on new rather than existing knowledge. A patent is explorative if at least 80% of its citations refer to new knowledge (all patents that the firm did not invent and all patents not cited by the firm's patents filed over the past five years). We then compute the percentage of explorative patents filed in a given year by the firm. This firm-year level variable is separately constructed for patents from the key technology class (Table 4 Panel B, Column 3) or the technology class defined as non-key (Column 7). We also measure the intensity with which a firm innovates based on existing knowledge using the variable *Exploitative*. A patent is classified as exploitative if at least 80% of its citations refer to existing knowledge. We then compute the percentage of exploitative patents filed in a given year by the firm.

Panel B of Table 4 indicates that activists bring changes only in explorative strategies in technological areas that are central to the target firm, where the percentage of explorative patents in target firms' key technology classes increase by about 4% (Column 3, significant at the 1% level) relative to the matched firms post-intervention. Changes in exploitative patents in the key class and changes in both types of patents in the non-key classes are all far from being significant. Overall, the evidence is consistent with the view that, post-intervention, the improvement in innovation productivity is more pronounced among firms that started with a more dispersed innovation portfolio but then refocus innovative activities within the core technological capabilities while seeking to move beyond knowledge they generated in the past.

4.2. Reallocation of patents

We now turn to a more precise examination of the characteristics of patents that are reallocated and their performance post sale. We hypothesize that, in general, the gain in innovation efficiency may be accomplished by a redrawing of the firm boundaries, mostly via selective asset sales and matching of the currently unproductive assets to more suitable owners.

We test this hypothesis by examining the reallocation of patents owned by target firms (and their matched firms) through patent transactions, especially the sale of patents and the resulting changes in patent portfolios and innovation efficiency.[18] We begin with the same specification as in Eq. (1), but replace the dependent variable with patent transactions, measured as the annual number of patents purchased (sold) by a firm, scaled by the total number of patents owned by the firm at the beginning of the year. The construction of the dependent variable necessarily constrains the relevant sample to firm-year observations in which firms own at least one patent. As before, we include year fixed effects in all specifications and either industry or firm fixed effects. Results are reported in Panel A of Table 5.

The coefficient on the interaction term, $I(Target_i) \times I(Post_{i,\ t})$, in Columns 1 and 2 of Panel A, reveals that target firms increase patent sales post-intervention at an annual rate of approximately 0.64%, as compared to the unconditional annual sale rate of 0.8%. As to patent purchases, the same coefficient in Columns 3 and 4 is insignificant. The question that naturally follows is, then, which characteristics of patents, especially with regard to their relation to the core competence of the firm, are associated with a higher propensity of being sold? Panel B of Table 5 offers an answer. Here, the sample consists of patent-firm-year (j, i, t) level observations, and the dependent variable, $I(PatentSale_{j,i,t})$, is a dummy variable set to one if a patent sale occurred in a given year. The key independent variable $Distance_{j,i,t}$, developed in Akcigit et al., (2016), measures the distance between a given patent j and firm i's overall patent portfolio in a year. The two columns vary in the value (0.33 and 0.66) of the weighting parameter ι used in constructing $Distance_{j,\ i,\ t}$[19]. $Before_{i,\ t}$ is a time dummy variable equal to one if year t falls into the $[t-3,\ t-1]$ range relative to the event year, and similarly, $After_{i,t}$ is a dummy variable equal to one if year t falls into the $[t,\ t+3]$ range. Both $Before_{i,t}$ and $After_{i,t}$ are coded as zero for all observations associated with the matched firms. All specifications include year and patent vintage fixed effects. We adopt the linear probability model in order to accommodate the high-dimensional fixed effects.

[18] Online Appendix 2 provides a detailed example of Starboard Value's activist intervention at AOL, Inc. in which the activist sought to reallocate the target firm's patent portfolio.

[19] The caption to Table 5 provides a detailed description of the variable *Distance* and the parameter ι.

Table 5

Patent transactions around hedge fund activism.

This table provides evidence on patent transactions around hedge fund interventions. Patent transactions, reported in Panel A, are modeled using the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_{SIC3/i} + \beta_1 \cdot I(Target_i) \times I(Post_{i,t}) + \beta_2 \cdot I(Target_i) + \beta_3 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t}.$$

The sample consists of the hedge fund targets and matched firms, as described in Table 2. We include observations from five years prior to and five years post the activism event year (the pseudo-event year). The dependent variables are the numbers of patents bought or sold by a firm in a given year, scaled by the total patents owned by the firm. Patent transactions are identified from the United States Patent and Trademark Office (USPTO) and accessed through the Google Patent database. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism and *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). Control variables include the natural logarithms of firm market capitalization and firm age. All specifications also include year and industry (or 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.

Panel B analyzes the determinants of patent sales using a linear probability model. The key variable of interest is *Distance (Patent to firm),* which measures the distance between a given patent and the firm's overall patent portfolio, based on the methodology developed in Akcigit et al., (2016). The distance between a technology class X and Y is constructed as

$$d(X,Y) \equiv 1 - \frac{\#(X \cap Y)}{\#(X \cup Y)},$$

where $\#(X \cap Y)$ denotes the number of all patents that cite at least one patent from technology class X and at least one patent from technology class Y; $\#(X \cup Y)$ denotes the number of all patents that cite at least one patent from technology class X or at least one patent from technology class Y, or both. The distance of a patent *p* to a firm *f*'s technology stock is computed by calculating the average distance of *p* to each of the patents owned by *f*. Specifically,

$$d(p,f)_\iota = \left[\frac{1}{\|P_f\|} \sum_{p' \in P_f} d(X_p, Y_{p'})^\iota \right]^{1/\iota}$$

where ι is the weighting parameter and $0 < \iota \leq 1$. P_f denotes the set of all patents that were ever invented by firm *f* prior to patent *p*, and $\|P_f\|$ denotes its cardinality. We follow Akcigit et al., (2016) and use $\iota\iota = 0.33$, 0.66 for our analyses below with two columns that vary in the value of the weighting parameter. *Before* is a dummy variable equal to one for event years $t-3$ through $t-1$. *After* is a dummy variable equal to one for event years from t to $t+3$. Both *Before* and *After* are coded as zero for all observations belonging to the matched firms. All specifications include year, patent vintage, and patent technological class (or 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.

Panel A: Patent transaction intensity around hedge fund activism

	(1)	(2)	(3)	(4)
	$\frac{\text{Patent sales}}{\text{Patents owned}}$ (in %)		$\frac{\text{Patent purchases}}{\text{Patents owned}}$ (in %)	
I(Target) × I(Post)	0.641**	0.691**	0.012	0.084
	(2.171)	(2.428)	(0.085)	(0.633)
I(Target)	−0.350		0.140	
	(−1.257)		(1.073)	
I(Post)	0.250	−0.212	0.141	−0.037
	(0.973)	(−0.837)	(1.272)	(−0.330)
ln(MV)	0.007	−0.023	0.089***	0.024
	(0.159)	(−0.218)	(4.285)	(0.615)
ln(Age)	−0.276***	0.420	−0.261***	−0.287
	(−2.711)	(1.424)	(−3.806)	(−1.495)
Observations	9,374	9,374	9,374	9,374
R-squared	0.028	0.143	0.029	0.163
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Panel B: Determinants of patent transactions

	(1)	(2)	(3)	(4)
	Patent sale (= 100%)			
	Distance measure ($\iota\iota = 0.33$)		Distance measure ($\iota\iota = 0.66$)	
Distance (Patent to firm)	0.470***	0.529***	0.710***	0.701***
	(7.990)	(8.503)	(10.647)	(9.697)
Distance × After	0.132**	0.283***	0.147*	0.163*
	(2.247)	(4.723)	(1.712)	(1.918)
Distance × Before	−0.090	−0.260***	−0.114*	−0.364***
	(−1.601)	(−4.444)	(−1.787)	(−5.422)
After	0.443***	1.082***	0.423***	0.932***
	(10.858)	(9.239)	(11.238)	(7.115)
Before	−0.383***	−0.126**	−0.523***	−0.141***
	(−5.735)	(−2.323)	(−7.208)	(−3.715)
Observations	929,613	929,613	929,613	929,613
R-squared	0.010	0.037	0.010	0.037
Year FE	Yes	Yes	Yes	Yes
Patent Age FE	Yes	Yes	Yes	Yes
Tech Class FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes

The negative (positive) coefficients on $Before_{i,\,t}$ ($After_{i,\,t}$) in Panel B affirm the results from Panel A that target firms engage less (more) in selling patents in the period prior to (after) the arrival of activists. Consistent with Akcigit et al., (2016), the positive estimate on $Distance_{j,\,i,\,t}$ indicates that firms are generally more likely to sell a patent that is distant from the firm's portfolio. Importantly, this effect is weaker for target firms pre-intervention when the coefficient on $Distance_{j,\,i,\,t} \times Before_{i,\,t}$ is negative and significant in three out of four specifications. However, the propensity to sell distant patents is markedly stronger for target firms post-intervention as manifested by the positive and significant (at the 5% or 10% levels) coefficient on $Distance_{j,\,i,\,t} \times After_{i,\,t}$.

In sum, targets of hedge fund activists are associated with a heightened propensity to sell patents peripheral to the firms' core expertise, adding to the consistent evidence that hedge fund interventions serve to refocus the scope of innovation. While we do not find that the rate of patent purchases by target firms differs from their matched firms (Columns 3 and 4 of Panel A, Table 5), we report in the Online Appendix Table A17 that purchases by target firms tend to take place with patents whose distance from the patent portfolio is smaller than that of purchases made by matched firms. That is, the refocusing takes place both with patent sales and purchases.

We next probe further as to whether the sale of patents also represents efficient reallocation of innovation resources. We construct a patent-year (j, t) level sample by merging the patent transaction database with the NBER patent database for citation information. The sample includes all the patents retained and sold by both targets and their matched firms, which allows us to estimate the dynamics of yearly citations around patent transactions and to compare the difference between targets and non-targets. The regression specification is as follows:

$$Citation_{j,t} = \sum_{k=-3}^{+3} \beta_k \cdot d[t+k]_{j,t} + \gamma \cdot Control_{j,t} + a_j + a_t + e_{j,t}. \quad (4)$$

The dependent variable is the number of new citations an existing patent j receives in year t. The key independent variables, $d[t+k]_{j,t}$, $k=-3,\ldots,+3$, are dummy variables for observations that are k years from the event year, where an event is the sale of a patent by either a target firm within two years after intervention or a non-target firm within two years after the pseudo-event year. The control variable is log patent age. The regression incorporates year and patent fixed effects to absorb time- and patent-specific unobservable characteristics, and we cluster standard errors at the patent level. The regression results are reported in Table 6.

The coefficients on $d[t+k]_{j,t}$, $k=-3,\ldots,+3$ for target firms in Column 1 exhibit a "V" shape pattern centered on the year of sale, as plotted in Fig. 2 Panel A. In the three years before the sale the impact of the patents eventually sold post hedge fund activism is statistically equivalent to their own long-run average, but in the subsequent three years there is a significant deterioration, as evidenced by the significant F-statistics testing the difference, $d[t]$ – $d[t-3]$. These patents are sold at the trough in terms of annual citations, but then regain the pace of diffusion afterwards under the new owner. In fact, the significant F-statistics on the difference suggest annual citations to target firms' patents that are sold are higher than the levels in the year of sale. Column 2 of Table 6 provides the regression results following patent sales at non-target matched firms. Citations to patents that will be sold see a small and insignificant decline prior to the sale, $d[t]$ – $d[t-3]$. As plotted in Panel B of Fig. 2, post sale, the number of citations for these patents remains essentially flat. Importantly, the difference-in-differences analysis for the post-sale performance shows that the gain is significantly higher for target firms than non-target firms.

The evidence presented above is consistent with the hypothesis that target firms' patents were reallocated efficiently subsequent to the arrival of hedge fund activists. It is also, however, subject to an alternative interpretation favored especially by the critics of hedge fund activism: the activists are short-termists who force target firms to divest valuable assets, harming long-term firm value. Absent an instrument that would provide exogenous variation in patent sales we instead proceed to explore plausible hypothetical counterfactual scenarios that are all meant to approximate the counterfactual state in which the sold patents were retained by the target, and all incorporate the possibility that patents sold post-intervention were inherently better along unobservable dimensions.

More specifically, we perform the same analysis on three constructed counterfactuals for patents sold post-intervention: (1) the best (top quintile) patents retained by the matched control firms in terms of increases in citations over the following three years; (2) the best (top quintile) patents retained by the target firms. Both of these counterfactuals provide useful information on the dynamics of successful patents that target and control firms elected to retain; and (3) patents that the target firms did not sell, matched to patents sold using a propensity-score-matching algorithm based on patent application year, total citations received prior to the activism, three-year citation trend, and the distance to the firm's technology (as used in Table 5). The dynamics of citations of these three scenarios are shown in Columns 3 to 5 of Table 6, respectively.

Consider first the difference-in-differences analysis comparing the post-sale performance of patents sold by target firms (Column 1) to the best patents held by the matched control firms (Column 3). We find a significant incremental improvement (at the 5% and 10% levels) even relative to this stringent counterfactual. That is, the performance of the control firms' best patents should provide a high hurdle for the citations of the target firm's sold patents had these not been sold. The incremental improvement is therefore consistent with an efficient reallocation. We find similar patterns when using the counterfactual of best patents retained by the target firms themselves (Column 4). When comparing Columns 1 to 5, which examines patents that the target firms elected not to sell that are matched closely on the main observable attributes of the patents that were sold, we find that the propensity-score-matched retained patents share the same decline in cita-

Table 6
Citation dynamics of patents sold subsequent to hedge fund activism.
This table documents the dynamics of citations around patent sales by target firms, patent sales by matched firms, and citations to patents under three more counterfactual scenarios. Patent sales are restricted to within the first two years of the activist intervention (or the pseudo-event year). The regression specification, at the patent (j)-year (t) level, is as follows:

$$Citation_{j,t} = \sum_{k=-3}^{+3} \beta_k \cdot d[t+k]_{j,t} + \gamma \cdot Control_{j,t} + a_j + a_t + e_{j,t}.$$

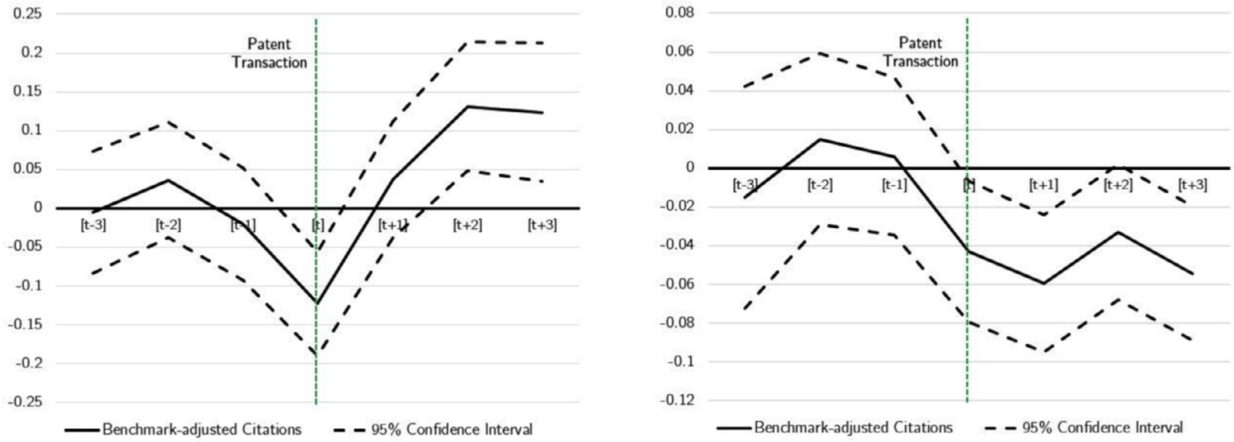
Column 1 provides the regression results for patents sold by target firms. Column 2 provides similar evidence but for patents sold by matched firms. In Column 3 we report the citation dynamics of the top patents held by matched firms, defined as patents whose citation increase over the ensuing three years ranks in the top quintile among all patents held by the matched firm. Column 4 reports the citation dynamics of the top patents held by the target firm and we define the target firm's top patents analogously. Column 5 presents evidence based on target firm's patents that the target chose to retain matched to the patents sold after the event year. The matching algorithm selects from patents owned by the targets but are not sold after the activism based on patent application year, total citations received before activism, three-year citation trend, and the distance to the firm's technology (as used in Table 5). The dependent variable is the number of new citations a patent receives in a given year. The dummy variable $d[t+k]$ is equal to one if the observation is k years from the sale of a patent, and zero otherwise. At the bottom of each panel we report estimates for the change in citations in the periods before and after the event year, $[t]$-$[t-3]$ and $[t+3]$-$[t]$ and the associated p-values. In Columns 2 to 5 we test for differences in the trends in the period after the sale, measured relative to the trend in citations by patents sold by target firms reported in Column 1, ($[t+3]$-$[t]$) x (Targets - Counterfactual). We control for the natural logarithm of patent age. All specifications include year and patent fixed effects. In all panels, 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) Patents sold by target firms	(2) Patents sold by control firms	(3) Best patents kept by control firms	(4) Best patents retained by target firms	(5) Retained PSM-matched patents within the target
$d[t-3]$	−0.005	−0.015	−0.036	−0.009	−0.006
	(−0.124)	(−0.513)	(−1.334)	(−0.106)	(−0.122)
$d[t-2]$	0.036	0.015	−0.014	0.012	−0.024
	(0.956)	(0.666)	(−0.441)	(0.233)	(−0.981)
$d[t-1]$	−0.020	0.006	−0.057*	0.022	−0.018
	(−0.546)	(0.293)	(−1.770)	(0.511)	(−0.805)
$d[t]$	−0.123***	−0.043**	−0.033	0.024	−0.071**
	(−3.630)	(−2.324)	(−1.453)	(0.641)	(−1.997)
$d[t+1]$	0.037	−0.060***	0.009	0.077**	−0.015
	(0.966)	(−3.299)	(0.304)	(2.204)	(−0.516)
$d[t+2]$	0.131***	−0.033*	0.056*	0.144***	−0.046
	(3.095)	(−1.847)	(1.718)	(3.334)	(−1.266)
$d[t+3]$	0.124***	−0.054***	0.065**	0.194***	−0.025
	(2.711)	(−3.074)	(2.413)	(5.075)	(0.747)
Observations	1,291,915	1,291,915	1,291,915	1,291,915	1,291,915
R-squared	0.447	0.449	0.451	0.441	0.438
Year FE	Yes	Yes	Yes	Yes	Yes
Patent FE	Yes	Yes	Yes	Yes	Yes
F-test					
$[t]$-$[t-3]$	6.67	0.72	0.04	0.24	3.47
p-val	0.01%	39.50%	83.84%	79.66%	5.83%
$[t+3]$-$[t]$	23.31	0.24	5.02	12.33	1.33
p-val	0.00%	62.47%	2.72%	0.00%	24.31%
($[t]$-$[t-3]$) x (Targets - Counterfactual)	–	0.00	2.53	4.22	0.83
p-val	–	96.92%	11.23%	5.13%	34.25%
($[t+3]$-$[t]$) x (Targets - Counterfactual)	–	6.12	4.74	8.37	5.14
p-val	–	1.34%	2.91%	0.00%	2.23%

tions in the year of the sale but no evidence of a rebound in citations.

The evidence presented above, though supportive of an inference for incremental improvement, still rests on matching based on observable attributes, and does not completely rule out an alternative hypothesis that the documented relation is driven by unobservable patent characteristics. It is worth noting that several pieces of evidence should already alleviate such a concern. First, Table 5 Panel B provides information on the distance of a patent to the selling firm's overall innovation portfolio as a factor driving the decision to sell the patent. Akcigit et al., (2016) find that patents that are more distant from the firm's overall patent portfolio are typically of lower strategic value. Consistent with this argument, we find that the patents sold post hedge fund activism are more peripheral patents to the selling firm, and are therefore unlikely to be highly valuable to the selling firm in the period subsequent to the targeting.

Second, additional analysis tabulated in Table A18 in the Online Appendix finds that the average annual citations between $t-3$ and $t-1$ (year t is the year of the sale), as well as the total citations up to year t, to patents sold by target firms differ significantly from those of the same counterfactual scenarios considered in Table 6. Average annual citations between $t-3$ and $t-1$ to the eventually sold patents is 0.248 whereas it is much higher at 0.964 for the best patents retained by the treated firms or 0.915 for the best patents retained by the control firms. Total citations up to year t



(A) Patent sales by targets of hedge fund activists

(B) Patent sales by matched firms

Fig. 2. Citation dynamics around patent transactions. This figure plots the coefficients β_k from the following regression at the patent (i)-year (t) level:

$$Citation_{i,t} = \sum_{k=-3}^{+3} \beta_k \, d[t+k]_{i,t} + \gamma \cdot Patent\ Age_{i,t} + \alpha_i + \alpha_t + \varepsilon_{i,t}.$$

$Citation_{i,\,t}$ is the number of new citations a patent receives in a given year. The dummy variable $d[t+k]$ is equal to one if the patent observation is k years from the sale of the patent, and zero otherwise. We run the regression separately for patents sold by target firms within two years following hedge fund intervention (left panel) and for patents sold by the propensity-score-matched non-target firms (right panel) within two years following the pseudo-event. We control for *Patent age* measured as the logarithm of the patent age in year t. We also include year and patent fixed effects, α_t and α_i. Standard errors are clustered at the firm level.

also show that citations to the sold patents are lower than the best patents retained by both target and control firms. These striking differences during the pre-sale period between patents that the treated firms decide to reallocate and the patents that the treated (and controls) chose to retain support the interpretation that the former are underperforming assets that are subsequently reallocated.

Overall, we consider the multiple counterfactuals and the additional analyses presented as consistent with the interpretation that, post-intervention, target firms reallocate some of the underperforming and peripheral patents to better-suited users, and none of them supports the alternative hypothesis that targets sell valuable assets that would have performed well in-house had these patents been retained.

4.3. Redeployment of human capital

The dynamics of patent transactions following hedge fund intervention suggest that a similar pattern could also exist in human capital redeployment. After all, a large portion of R&D expenditures goes into hiring and incentivizing innovators, and early research has demonstrated that innovative human capital is an important determinant of firm performance (Seru, 2014; Bernstein, 2015).

Following Bernstein (2015), we use the HBS patent and inventor database to classify three groups of inventors: a "leaver" is an inventor who leaves her firm during a given year, a "new hire" is an inventor who is newly hired by a given firm in a given year, and a "stayer" is an inventor who stays with her firm during a given year. For all three groups, we necessarily require that the inventor generate at least one patent prior to the year of intervention and generate at least one patent after the year of intervention.[20]

A two-step analysis sheds light on how hedge fund activism is associated with human capital redeployment. In the first step, we test whether hedge fund activism is associated with higher inventor mobility using the same difference-in-difference framework as Eq. (1), except that we replace the dependent variable with the logarithm of the number of leavers or new hires (plus one). The results are reported in Table 7, Panel A. The insignificant coefficients on $I(Target_i)$ indicate that the unconditional rate of innovator departures and arrivals at target firms is similar to that of their matched peers. Nevertheless, within the five-year period subsequent to the arrival of activist hedge funds, the rate of innovator departures (arrivals) increases significantly (at the 10% and 1% levels) relative to the control firms by 6.2% (8.6%) in the specification with firm fixed effects.

Next, we trace the productivity gains for all three groups of inventors post-intervention. The sample now consists of inventor-firm-year (l, i, t) observations. The regression specification is the same as in Eq. (1) except that the dependent variable is now the change between two, three-year periods in the number of new patents (the first three columns of Table 7, Panel B) or new citations per patent (the last three columns). The first-difference speci-

[20] Bernstein (2015) points to a limitation of the HBS patent and inventor database in that the relocation of an inventor is not recorded unless the transitioning inventor files patents in a new location. As a result, we are effectively constraining the sample to "frequent" patent filers, that is, we require at least one patent filing both before and after the intervention or relocation. More generally, the method is more applicable to firms where most employees involved in R&D activity aim at patenting.

Table 7
Inventor mobility around hedge fund activism.
This table analyzes inventor mobility around hedge fund interventions (Panel A) and associated changes in inventor productivity subsequent to inventor turnover (Panel B). The sample consists of hedge fund targets and matched firms, as described in Table 2. A "leaver" is an inventor who leaves her firm during a given year, who generated at least one patent in the firm before the year she left, and who generates at least one patent in a different firm afterwards. A "new hire" is an inventor who has been newly hired by a given firm in a given year, who generated at least one patent in a different firm before the year of hiring, and who generates at least one patent in the current firm afterwards. A "stayer" is an inventor who stays with her firm during a given year and who generated at least one patent both before and after the year of intervention (or the pseudo-event year). An inventor is considered as generating a patent if she files for a patent during the relevant time period and that request is ultimately granted. Panel A adopts the following difference-in-differences specification at the firm (i)-year (t) level:

$$y_{i,t} = \alpha_t + \alpha_{SIC3/i} + \beta_1 \cdot I(Target_i) \times I(Post_{i,t}) + \beta_2 \cdot I(Target_i) + \beta_3 \cdot I(Post_{i,t}) + +\gamma \cdot Control_{i,t} + \varepsilon_{i,t}.$$

I(Target) is a dummy variable indicating whether the firm is a target of hedge fund activism and *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). Control variables include the natural logarithms of firm market capitalization and firm age. The dependent variables in Columns 1 and 2 are the natural logarithm of the number of leaving inventors (plus one) and the number of newly hired inventors (plus one), respectively. All the specifications include year and industry (or firm) fixed effects. Panel B adopts a similar specification as in Panel A but at the inventor-year level on two cross sections. The dependent variable is the change in an inventor's productivity between two three-year periods. In the first cross section, the difference is taken between $[t-3, t-1]$ and $[t-6, t-4]$, where t is the event (or pseudo-event) year. In the second cross section (defined as post-event, or $I(Post)=1$), the difference is taken between $[t, t+2]$ and $[t-3, t-1]$. 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.

Panel A: Inventor mobility subsequent to hedge fund activism

	(1) ln(1 + Leavers)	(2) ln(1 + Leavers)	(3) ln(1 + New hires)	(4) ln(1 + New hires)
I(Target) × I(Post)	0.067*	0.062*	0.081***	0.086***
	(1.831)	(1.664)	(2.925)	(3.184)
I(Target)	0.034		0.008	
	(0.889)		(0.266)	
I(Post)	−0.044	−0.019	−0.071***	−0.047**
	(−1.365)	(−0.812)	(−2.791)	(−2.399)
ln(MV)	0.094***	0.025***	0.080***	0.017***
	(9.939)	(2.613)	(10.090)	(2.674)
ln(Age)	0.019	0.053	0.003	0.004
	(0.943)	(1.275)	(0.200)	(0.144)
Observations	9,817	9,817	9,817	9,817
R-squared	0.298	0.618	0.267	0.545
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes

Panel B: Change in inventor productivity subsequent to hedge fund activism

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ New patents (Inventor-level)			Δ New patent citations (Inventor-level)		
	Stayer	Leaver	New hire	Stayer	Leaver	New hire
I(Target) × I(Post)	1.088***	1.121*	0.763**	1.958***	3.239*	0.510
	(8.096)	(1.867)	(2.418)	(7.380)	(1.881)	(1.381)
I(Target)	0.530	0.411	0.140	−0.500	−1.013	−1.367
	(1.628)	(0.975)	(0.397)	(−1.045)	(−0.892)	(−1.202)
I(Post)	0.852	0.623	−0.335	−0.739	−1.059	−0.949
	(1.550)	(0.998)	(−0.673)	(−0.643)	(−0.729)	(−0.651)
Δln(MV)	0.155**	0.191	0.245*	−0.254	−1.717***	−0.478
	(2.544)	(1.258)	(1.906)	(−1.135)	(−2.995)	(−0.862)
Observations	36,418	1,717	2,836	36,418	1,717	2,836
R-squared	0.113	0.215	0.163	0.220	0.504	0.362
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

fication automatically subsumes an innovator fixed effect. The sample includes all inventors who appear over the three years before the event and in the event year who can be categorized as "stayers," "leavers," or "new hires," and essentially pools two cross sections. Inventors who cannot be categorized into the three categories are excluded from the sample. In the first cross section, the difference is taken between $[t-3, t-1]$ and $[t$-6, $t-4]$, where t is the event (or pseudo-event) year. In the second cross section (defined as post-event, or $I(Post)=1$), the difference is taken between $[t, t+2]$ and $[t-3, t-1]$. All regressions include year fixed effects.

Columns 1 and 4 show that "stayers" experience significantly higher improvement in productivity—both in terms of the quantity and quality of patents they file (1.088 more new patents and 1.958 more citations per patent) post hedge fund intervention—compared to "stayers" at matched firms during the same period. Such a phenomenon is consistent with both a selection effect where the less productive inventors leave the firms, raising the average of the remainder, or a treatment effect in which the stayers have access to more resources and/or managerial support after the reduction. Both effects reflect favorably on the retention of innovators post hedge fund intervention.

Similar to the ex post performance of sold patents, the "leavers" also fare better at their new employers, although these effects are significantly weaker. Both the increase in their new patents and the increase in the impact of their new patents are positive but marginally significantly higher than their peers (Columns 2 and 5). More specifically, inventors who have departed shortly after hedge fund intervention later produce patents that receive about three citations per patent more than inventors in the control sample, suggesting that these individuals were able to land on "greener pastures." Finally, Columns 3 and 6 show that "new hires" perform at or above par: They generate an abnormal number of new patents relative to new hires at non-target firms, but there is no significant improvement in the quality of these new patents.

These results, although striking, do not directly refute that a similar improvement would have occurred had the "leavers" remained as "stayers." However, if the alternative hypothesis were to hold, then the coefficient on $I(Target_i) \times I(Post_{i,t})$ would be underestimated for "stayers" because the departure induces an unusual negative survivorship bias (i.e., the better inventors leave). Thus, the performance improvement of at least one of the "stayers" or "leavers" cannot be attributed to selection.

4.4. Incentives, governance, and changes in leadership

The outcomes documented in previous sections are unlikely to have taken place without an improvement in the overall governance and leadership at the target firms or without proper incentives to management and key personnel. This section reports on two analyses in which we explore this channel.

First, we examine how hedge fund intervention impacts managerial career concerns and risk tolerance, which have been documented as important factors for motivating innovation in the literature (Manso, 2011; Aghion et al., 2013). Using executive compensation data from ExecuComp, Table 8, Panel A confirms a major finding in previous studies (e.g., Brav et al., 2008) that CEO turnover surges by 12%–13% post-intervention. What is more important, however, are the forward-looking incentives that are set for the CEOs that are either retained or hired in the period after the arrival of activists. To this end, Panel B demonstrates that CEOs that are *newly* appointed post-intervention actually enjoy significantly *longer* tenure (by about a year and a half) compared to new CEOs hired by the matched firms. In other words, CEOs newly hired shortly after the intervention enjoy better-than-usual job security, which may partially relieve career concerns. A similar pattern holds for CEOs who are retained after the activism. Panels C and D further show that both CEOs and Chief Technology Officers (CTOs) have a higher ownership share post-intervention relative to the same insiders at the control firms, consistent with the evidence in Clifford and Lindsey (2016) and Keusch (2016). Overall, incentives tend to change in the direction of more "skin in the game" and are supportive of risk taking, which may serve to better motivate investment in innovation (Lerner and Wulf, 2007).

Second, we examine how activists facilitate the dissemination of specific knowledge that encourages or promotes innovation. The current literature (Gantchev et al., 2017; Aslan and Kumar, 2016) finds that there is an industry clustering of targeting by activists. We confirm the pattern in our sample and find that it is even stronger among operational- (rather than financial-) oriented interventions.[21] As such, activists—both individually and collectively—develop expertise about industry trends and competitive situations of the main players, acquire knowledge to assess individual targets against industry benchmarks, and disseminate best practices. Moreover, activists, as economically driven outsiders, can be more objective (and are certainly less beholden to biases related to sunk cost, overconfidence, and managerial entrenchment) in helping to make retention/reallocation decisions of innovative resources and outputs.

Using the NYSE Director Database, which covers all publicly traded firms from 2000 to the end of our sample period, we ask whether technological expertise is added to the board via board turnover post-intervention. We first find that target boards change by an additional 1.1 new directors and 0.5 departures, compared to the matched firms. We then apply a textual analysis on the biographies of directors, extracting their area of expertise in specific categories (see the caption of Table 9 for details). Table 9 compares the expertise in major areas (including technology and innovation) of directors newly appointed within the three-year window post the activist intervention and those new directors in matched firms over the same time period. We find that new directors at target firms have overall better credentials in the post-intervention period: "activist directors" are more likely to have financial and operational experience; and, more important to this study, they are 5% more likely to have expertise in innovation, as identified by keywords in their bios.[22] The difference is statistically

[21] For example, Starboard Value targeted two pharmaceutical companies, Perrigo and Depomed, in 2016, following Ichan's earlier campaigns targeting Forest Laboratories and Sanofi, and Relational Investors' engagement with Hologic. The same wave happened in the energy sector in 2014–2016.

[22] The list of keywords in this category includes: Technology, research, R&D, network, engineer, product development, software, science, scientific, and patent.

Table 8
Executive career concern and incentives.
This table reports CEO turnover, job security, and the incentives provided by compensation for the subsample of innovative target firms defined as firms that filed for at least one patent that was eventually granted prior to the year of the hedge fund intervention with at least one positive R&D expenditure within the five-year window prior to the intervention and for the control sample. The control sample is formed by matching each event firm to the non-event innovative firm from the same year and same industry (two-digit SIC) with the closest propensity score, where the propensity score is estimated using log firm size, market-to-book ratio, return on assets (ROA) measured at $t-1$, and the change in the target firm ROA measured between years $t-3$ and $t-1$. In Panel A, we report the probability of CEO turnover during the three-year period before and after the event (and pseudo-event for control firms), calculated as the percentage of firms that have a CEO turnover during those three-year periods. In Panel B, we report the tenure of both newly appointed CEOs and CEOs who were retained after the hedge fund intervention (or pseudo-event). The tenure of the newly appointed CEOs is calculated as the average tenure. Panel C examines the ownership level of CEOs measured as the number of shares owned by CEO divided by the number of shares outstanding. Panel D presents the ownership level of technology officers. We identify technology officers' ownership by combining the HBS inventor database and the SEC Form 4 insider trading data, both of which are described in the paper. Through name matching, we identify all the officers who are inventors (innovative officers), and remove those innovative officers with the title of "CEO" or "CFO." The remaining individuals are considered to be officers with technological expertise. We measure insider ownership level of technology officers as the number of shares owned by the officer divided by the number of shares outstanding. We report the t-statistics for the differences in mean values between targets and matched firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Hedge fund targets	Matched firms	*Treated-control difference*
Panel A: Turnover			
% of Firms with at least one CEO turnover within the 3 years prior to the intervention	22.33%	26.44%	*−4.11%*
% of Firms with at least one CEO turnover within the 3 years subsequent to the intervention	32.69%	20.25%	*12.44****
Post-Pre difference	*10.36%****	*−6.19%*	*16.55%****
Panel B: Job security			
Tenure of newly appointed CEOs within 3 years prior to the intervention (in days)	1693	1897	*−204*
Tenure of newly appointed CEOs within 3 years subsequent to the intervention (in days)	2076	1773	*303**
Post-Pre difference	*383***	*−124*	*507***
Tenure of incumbent CEOs surviving first 3 years *After* event (days)	2173	1928	*245*
Panel C: Ownership level of CEOs			
Insider ownership of CEOs within 3 years prior to the intervention	0.63%	0.64%	*−0.01%*
Insider ownership of CEOs within 3 years subsequent to the intervention	0.78%	0.61%	*0.17%**
Post-Pre difference	*0.15%**	*−0.03%*	*0.18%**
Panel D: Ownership level of technology officers			
Insider ownership of technology officers within 3 years prior to the intervention	0.12%	0.11%	*0.01%*
Insider ownership of technology officers within 3 years subsequent to the intervention	0.18%	0.11%	*0.07%**
Post-Pre difference	*0.06%**	*0%*	*0.06%**

significant. The tightening of governance, enhanced incentives, and improved technological knowledge at the board level are likely to promote value creation through innovation.

5. Causality

The consistency of results in the previous sections from different viewpoints provides support for the view that the changes in innovation policies and outcomes are potentially due to hedge fund intervention. A priori, it is difficult to justify the launching of an activism campaign if the same outcome would have taken place had the activist merely picked the stock of the target firm and remained as a passive investor. It is hard to argue that activist funds would willingly hold undiversified positions for a considerable length of time (two years) and be subject to costly engagements (Gantchev, 2013) if these were not necessary means to achieve their goals. It is also important to point out that we purposely do not focus on the effect of hedge fund activism on a *randomly* chosen target firm since selective targeting is central to the success of the investment strategy. The more relevant treatment effect is thus whether the same changes would have taken place had the hedge funds remained passive owners in the same targets. We thus conduct three tests to separate treatment (intervention) from mere stock-picking.

5.1. Mean reversion and managerial voluntary changes

One competing view holds that activists are informed and sophisticated investors and are therefore able to target firms whose general business strategies—which include innovative strategies—were about to go through voluntary

Table 9
Expertise of newly appointed board members.
This table studies the expertise of newly appointed board members of hedge fund target and control firms. Each observation is a board member newly appointed by these firms within the three-year window post-intervention (or pseudo-event). We collect each board member's biographical information from the NYSE Director's Database. The data are from 2000 to 2013, covering the full sample of directors of publicly traded firms.
We perform a textual analysis on the biography of board members to extract their expertise in seven categories—academic, accounting, innovation, legal, management, marketing, and operation. Specifically, for each area of expertise, we search for the following keywords (both in capital and lowercase letters, expressed here using lowercase letters):

- *Innovation*: technology, research, r&d, network, engineer, product development, software, science, scientific, patent;
- *Academic*: professor, dean, lecturer;
- *Financial*: account, actuary, asset management, acquisition, audit, broker, buyout, capital, credit, cfo, cpa, debt, equity, finance, fund manager, invest, leverage, lend, liquidation, managing director, merger, restructuring, tax, treasurer;
- *Management*: supervisor, management, head, president, ceo, chair, executive;
- *Operation*: business, communications, operations, coo, chief operating officer, hr, human resources, enterprise risk, manufacturing, strategy;
- *Marketing*: sales, marketing, merchandise;
- *Legal*: attorney, compliance, lawyer, counsel, jd, juris.

Expertise is a dummy variable indicating whether the board member has the specific expertise (one of the defining keywords of expertise appears at least once in the biographical information), and *Expertise score* measures the weight of such expertise by counting the frequency of related key words. We report the *t*-statistics for the differences in mean values between the target and control firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Targets	Non-targets	Difference	*t*-Statistic
Age	53.594	54.067	−0.473**	−2.049
Female	0.089	0.103	−0.014	−1.613
Independence	0.518	0.515	0.002	0.145
Expertise (Yes =1 or No = 0)				
Innovation	0.535	0.489	0.045***	3.014
Academic	0.046	0.043	0.003	0.475
Financial	0.595	0.552	0.043***	2.866
Management	0.841	0.830	0.011	0.947
Operation	0.664	0.636	0.027*	1.917
Marketing	0.180	0.182	−0.002	−0.133
Legal	0.118	0.119	−0.001	−0.107
Expertise score				
Innovation	0.952	0.852	0.100**	2.174
Academic	0.606	0.541	0.065	0.579
Financial	0.961	0.855	0.106***	2.746
Management	0.704	0.663	0.041**	1.980
Operation	0.917	0.882	0.034	0.994
Marketing	1.053	1.157	−0.104	−1.089
Legal	0.931	0.904	0.027	0.284

changes in the same direction.[23] After all, it is well known that target firms experience a deterioration in performance prior to hedge fund intervention. The subsequent recovery, including changes to innovation, could reflect a reversion to a long-run mean that is simply anticipated by the activist.

Our propensity-score-matching is structured to address one element in the mean reversion alternative by controlling for firm performance in event years $t-1$ and $t-3$, along with other attributes such as industry, firm size, and the market-to-book ratio. The propensity-score-matching suggests the quantity and quality of innovation do not rebound in the years that correspond to the post-intervention period captured by the sign of *I(Post)* in Table 3. Mean reversion in innovative performance does not take place. Any traces of mean reversion should manifest in a positive slope on *I(Post).* Instead, it is either negative and marginally significant, when we examine the number of new patents in Column 3, or insignificant, in Column 4, when we examine citations per patent.

Of course, activist hedge funds select which firms to target based on both observable and unobservable attributes, and it is possible that a propensity-score-matching omits some unobservable factors that drive subsequent changes in innovation. To address this issue, we consider the subsample of openly confrontational events in which management resisted the hedge fund's agenda. If we were to observe a positive treatment effect for this

[23] Consider the recent Trian vs. DuPont case, described in Footnote 5. Trian Partners spent roughly $8 million to launch a proxy battle against DuPont in May 2015, more than two years after its initial investment in the target company. The competing view predicts that the changes, which include director turnover, a $5 billion share buyback, a major cost-cutting initiative, and a spinoff (Chemours), would have taken place absent the activist's advocacy and insistence.

Table 10
Innovation subsequent to hostile hedge fund activism.
This table reproduces the analysis in Table 3 but with the subset of innovative targets of hostile engagements and their propensity-score-matched control firms. We report the dynamics of inputs to and outputs from innovation around these hostile interventions. We use the following difference-in-differences specification:

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

We include observations from five years prior to and five years post-intervention for both targets and matched firms. *I(Target)* is a dummy variable indicating whether the firm is a target of hedge fund activism, and *I(Post)* is a dummy variable equal to one if either the target firm or its matched control firm is within $[t+1, t+5]$ years after the activism event year (or 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 A. In Column 7 the dependent variable is the market value of new patents applied for during the year, calculated as the market responses to the patents' approval following Kogan et al., (2017). 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) ln(1 + # New patents)	(4) ln(1 + Ave.citations)	(5) Originality	(6) Generality	(7) Yearly innovation value ($M)
I(Target) × I(Post)	−0.135	−14.014*	0.148*	0.135*	0.018	0.009	14.997
	(−1.072)	(−1.930)	(1.686)	(1.718)	(1.015)	(0.579)	(1.533)
I(Post)	0.318	1.005	−0.047	0.031	−0.028	−0.006	−1.841
	(1.345)	(0.117)	(−0.692)	(0.412)	(−1.305)	(−0.344)	(−0.227)
ln(MV)	−0.409***	6.680**	0.077***	0.086***	0.024***	0.016**	−0.483
	(−5.598)	(2.523)	(3.080)	(3.201)	(3.748)	(2.575)	(−0.095)
ln(Age)	−0.085	−25.890***	0.057	0.050	0.032	0.027	15.449*
	(−0.357)	(−2.994)	(0.593)	(0.447)	(1.384)	(1.165)	(1.972)
Observations	2,143	2,143	2,143	2,143	649	537	649
R-squared	0.873	0.894	0.661	0.545	0.520	0.442	0.644
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

subsample it would be more challenging to attribute the changes to the incumbent management's voluntary and planned actions. We define hostile events as those in which the activist's tactics involve either actual or threatened proxy contests and lawsuits or shareholder campaigns of a confrontational nature (such as campaigns aiming at ousting CEOs), and in which activism encountered managerial resistance. Hostile events account for 23% of our sample, close to the figure for the entire sample of activism events (21%). The results are reported in Table 10. As with the results for the broader sample reported in Table 3, openly confrontational events experience a decline in R&D dollar expenditures (significant at the 10% level) while the slope on *R&D/Assets* is insignificant. Importantly, we see that target firms file for 14.8% more patent applications compared to the matched firms, controlling for both firm and year fixed effects (significant at 10%), while patents filed post-intervention by this subsample receive 13.5% more citations (significant at 10%) than patents filed by matched firms during the same period. The fact that events in which management tended to oppose the activist agenda see an effect of the same magnitude as the overall sample is consistent with the view that activists' agendas tend to influence, at least partially, their target firms' innovation.

5.2. 13G to 13D Switches: stock-picking vs. intervention

Our second test differentiates between activists' stock-picking ability, the skill to anticipate improving fundamentals at the target firm absent the activists' own effort, from post-event changes that are likely caused by the intervention. The legal framework for block ownership disclosure offers an ideal setting to separate the two. Investors holding beneficial ownership of more than 5% but below 20% for purely "investment purposes," i.e., with no intent to influence control or policies, are usually eligible to file a less stringent Schedule 13G form with the SEC instead of a Schedule 13D form (under the Exchange Act, Section 13(g) and Regulation 13D-G). A Schedule 13G (13D) filing can be equated to a passive (activist) position for identification purposes if the following two conditions hold: First, an investor who files a 13G cannot take actions that could be interpreted as influencing firm policies and control, including actively "communicating" with management regarding firm strategies; second, an investor with a passive stance would not want to file a Schedule 13D. The first condition is essentially the current law while the second condition is incentive compatible. Since Schedule 13D filings entail added legal obligations, including a much shorter period before disclosure is due and further details required in a disclosure, a true passive investor should not find it appealing to file a Schedule 13D.[24]

A small sample of "13G-to-13D" switches allows us to filter out the treatment effect by focusing on changes in firm performance subsequent to the switch versus that of firms held by hedge funds who keep the 13G status. A switch is required by law if a formerly passive investor decides that it may now want to take actions to influence target policies. Importantly, such a switch in the investor

[24] For example, Schedule 13D requires instant filing of an amendment if there is any "material" change in the activist's action, including ownership changes of 1% or more in either direction. Schedule 13G, instead, requires disclosure of less information, and allows for a longer delay in ownership disclosure, i.e., within 45 days after the end of the calendar year.

Table 11
Innovation subsequent to hedge fund activism— activists' switch in filing status from Schedule 13G to Schedule 13D. This table documents the dynamics of inputs to and outputs from innovation around changes in hedge fund filing status from a Schedule 13G form (passive block holding) to a Schedule 13D form (activist block holding). We use the following difference-in-differences specification:

$$y_{i,t} = \alpha_t + \alpha_i + \beta_1 \cdot I(13G\ to\ 13D)_i \times I(Post_{i,t}) + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t}.$$

The full sample includes all firms in which we observe the filing of a Schedule 13G form, and the subsample of switches includes those for which we observe a subsequent switch to a filing of a Schedule 13D. The sample is restricted to Schedule 13G filings made by activist hedge funds, defined as hedge funds that had filed at least one Schedule 13D at an innovative target firm in our sample, and further restricted to those firms that had filed at least one patent prior to the Schedule 13G filing. Finally, the sample includes observations from five years prior to and five years post filing. *I(13G to 13D)* is a dummy variable equal to one if there is a 13-G-to-13D switch for a firm during the year (as opposed to remaining with the Schedule 13G status). *I(Post)* is a dummy variable equal to one if the firm-year observation is within $[t+1,\ t+5]$ years after the event year, where the event year is the year of the Schedule 13G filing for the non-switchers or the year of the switch for the switch subsample. In Column 1 the dependent variable is R&D expenditures scaled by firm assets. In Columns 2 and 3 the dependent variables are the natural logarithm of patent counts (plus one) and the natural logarithm of citations per patent (plus one), respectively. $Control_{i,t}$ is a vector of control variables, including the natural logarithms of market capitalization and firm age. All specifications include firm, hedge fund, 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) ln(1 + # New patents)	(3) ln(1 + Ave.citation)
I(13G to 13D)	−0.101	0.116*	0.174**
	(−0.215)	(1.946)	(1.968)
I(Post)	0.008	−0.014	−0.009
	(0.064)	(−0.713)	(−0.304)
Controls	Yes	Yes	Yes
Observations	6,756	6,756	6,756
R-squared	0.899	0.631	0.573
Year FE	Yes	Yes	Yes
Hedge fund FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

stance usually does not come with significant ownership changes, providing an unusual setting in which the ownership (and hence stock-picking) does not interfere with intervention. Moreover, our identification comes narrowly from the same hedge fund-firm pairing, and therefore unobserved fund or firm heterogeneities are also filtered out with the fixed effects.

We begin with the sample of all firms in which we observe a 13G filing by one of the hedge fund activists that had intervened in one of the 553 innovative targets. We then identify the subsample of 13G filings in which there was a subsequent switch to a 13D filing (the "switch sample"). As with our previous setup, we keep only those firms that file for a patent at least once prior to the filing of a Schedule 13G and retain observations from five years prior to and five years post filing. There are 79 interventions in our sample in which the activist engagement is initiated as a 13G-to-13D switch. We then estimate the following specification:

$$y_{i,t} = \alpha_t + \alpha_i + \alpha_f + \beta_1 \cdot I(Post_{i,t}) \times I(13G\ to\ 13D)_i + \beta_2 \cdot I(Post_{i,t}) + \gamma \cdot Control_{i,t} + \varepsilon_{i,t}. \quad (5)$$

The dependent variable, $y_{i,t}$, is R&D expenditures scaled by firm assets, the natural logarithm of one plus patent counts, or the natural logarithm of one plus lifetime citations per patent. $I(Post_{i,t})$ is a dummy variable equal to one if the firm-year observation is within $[t+1,\ t+5]$ years after the year of the Schedule 13G filing for events in which there is no subsequent switch and the year of the switch to a Schedule 13D for the subsample of switches. $I(13G\ to\ 13D)_i$ is a dummy variable equal to one if the event is a switch and zero otherwise. $Control_{i,t}$ is a vector of control variables including market capitalization and firm age (both in logarithmic terms), and α_t, α_i, and α_f represent year, firm, and hedge fund fixed effects, respectively.

The regression results, reported in Table 11, indicate that, relative to the firms in which the hedge fund blockholders chose not to switch from a passive to an activist approach, target firms with a switch to a Schedule 13D file about 11.6% more patent applications (significant at the 10% level), and their patents collect 17.4% more citations (significant at 10%), controlling for firm size and age and including year and firm fixed effects. As with the main sample, we do not find that a switch leads to a change in R&D expenditures scaled by firm assets. Given that only the activist's stance, and not its ownership, changes at the switching point, the test provides a cleaner identification of the impact of activist intervention beyond mere stock-picking.

Table 12
Market reactions to patent grant announcements.
This table analyzes market reactions to the announcement of patent grants in the period before and after the arrival of hedge fund activists. Panel A provides summary statistics on the number and frequency of patent grants whose application dates by target firms (propensity-score-matched firms) all took place prior to the filing of a Schedule 13D (pseudo-event date for the controls). The time window [t−6, t−1] is defined as the six-month interval prior to the filing of Schedule 13D (pseudo-event date for the controls). The time window [t, t+6] is defined as the six-month time interval after the filing of Schedule 13D (pseudo-event date for the controls). *Total patent applications [t−48,t−1]* is the sample of patent applications, which were eventually granted, that target (control) firms applied for within the 48-month period prior to the event (pseudo-event). *Lag between application and grant dates* gives the median and standard deviation of the number of months between application and grant days. Panel B provides regression results for the change-in-price reaction to patent grant news from grant years *[t-N,t−1]* to *[t,t+N]* (*N*=3,6 months), using the following model,

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

The regression is at patent-level. Abnormal returns to patent grant news are measured by the five-day cumulative abnormal return centered on patent grant dates in basis points, benchmarked against the CRSP value-weight market return. In Column 1 and 2 the sample consists of all the patents applied for by the targets and control firms within 48-months prior to the event and subsequently granted within the 12-month (six-month) window around the Schedule 13D filing (pseudo-event date). *I(Target)* is a dummy variable indicating whether the patent belongs to a target of a hedge fund activist and zero if the patent belongs to the matched firm. The target firms' event date is assigned to their corresponding control firms as a pseudo-event date. *I(Post)* is a dummy variable equal to one if the patent is granted after the filing (or the pseudo-event date). Columns 3 and 4 report a similar analysis on a different sample of pooled event and control firms. The event sample is the subset of target firms for which activists switched their filings from a Schedule 13G to a Schedule 13D. The control sample consists of those innovative firms in which the same activists filed a Schedule 13G filing without a subsequent switch to a Schedule 13D filing. *I(13G to 13D)* is a dummy variable equal to one if there is a 13G-to-13D switch. *I(Post)* is a dummy variable equal to one if the patent is granted after the event, where the event is the day of the switch for the event firms and is the day of the Schedule 13G filing for the control firms. All specifications control for firm fixed effects and the monthly fixed effects of the patent application-grant lag. 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.

Panel A: Patent grant dates centered around hedge fund interventions

	Targets	Non-targets
Total patent applications [t−48,t−1]		
% of Patent grants [t-6,t−1]	9.22%	9.83%
% of Patent grants [t,t+6]	9.58%	9.77%
% of Patent grants [t−3,t−1]	4.63%	4.99%
% of Patent grants [t,t+3]	5.07%	4.85%
Lag between application and grant dates (months)		
Median	30	31
Standard deviation	17.83	18.40
Average lifetime citations	5.662	6.091
Number of firms	373	389

Panel B: Price reactions to patent grants

	Abnormal return (in bps)			
	(1)	(2)	(3)	(4)
Granting window (months relative to intervention)	[t−6,t+6]	[t−3,t+3]	[t−6,t+6]	[t−3,t+3]
I(Target) x I(Post)	32.928**	30.972*		
	(2.489)	(1.712)		
I(13G to 13D)			45.444**	36.473
			(2.353)	(1.253)
I(Post)	−3.335	4.782	−3.793	−8.332
	(−0.222)	(0.876)	(−0.331)	(−0.571)
Observations	4,885	2,527	3,338	2,384
R-squared	0.168	0.274	0.157	0.172
Monthly fixed effects of application-approval lag	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

5.3. Market response to patent grant announcements

The third test is designed to calibrate the value impact of hedge fund activism by exploiting the long and semi-random delay between the patents' application and grant dates. We first limit the sample of patents to those that were applied for by target firms prior to the arrival of the activist (or pseudo-event time for the controls). Table 12, Panel A shows that the median (average) time interval is about two and a half years (three years). The variance, at about one and a half years, is also sizable. Both the delay and variance are indistinguishable between targets and non-targets. One can also plausibly argue that the exact timing of a patent grant is not under the control of either the filer or the activist, nor should the activist possess superior information useful in predicting the exact date of patent approval.[25]

As such, patents that were filed during the four-year period prior to intervention (i.e., [t−48, t−1] months) *and* granted during the 12-month period around the intervention month (i.e., [t-6, $t+6$] months) were likely produced under very similar circumstances. However, if hedge fund activism has an impact on patent productivity, then the market should perceive that patents granted during [$t+1$, $t+6$] would be put into better use and hence are more valuable than those granted during [t-6, $t-1$]. Hence, a more positive stock market response to patents granted post-activism is indicative of a market belief that the patents produced during the same “old” regime are worth more under the “new” regime. Table 12, Panel B provides supportive evidence.

The dependent variable in all four regressions is the abnormal stock return over the five-day window centered around the patent granting date, where the abnormal return is defined as the buy-and-hold stock return of the firm in excess of the CRSP value-weighted market return. The sample in Column 1 includes all patents granted during the [t-6, $t+6$] (month) window around hedge fund activism and the sample in Column 2 shrinks the window to [$t-3$, $t+3$]. All regressions incorporate firm fixed effects, and the fixed effects for the length of time (months) between the patent application and grant dates. It is plausible that patent applications incurring a longer waiting time are disproportionately represented in the [$t+1$, $t+6$] (or [$t+1$, $t+3$]) group (i.e., $I(Post)=1$), and that the duration could be correlated with patent quality, notwithstanding the randomness in the exact timing of approval. Hence, the application-approval time lag fixed effects subsume all the unobserved heterogeneity correlated with the time to approval. The estimated coefficients on the key independent variable, $I(Target) \times I(Post)$, range from 31 to 33 basis points (significant at the 10% and 5% levels, respectively), suggesting that the market value of patents granted goes up significantly post-intervention, even though the patents were produced and filed before the arrival of the activists.[26] The last two columns of Table 12, Panel B apply the same regression to the smaller subset of activism events that are 13G-to-13D switches. Again, the market reaction to patent grants during the post-switch period is about 36 to 45 basis points higher, though with lower significance due to the much smaller subsample of events.

One might argue that hedge funds might selectively target firms with high-impact patents in the pipeline for formal approval based on public or private information about patent quality. Note that pending patent applications are public information, hence the additional information about pending patent quality revealed by the hedge fund action should be impounded in the stock price during the activism announcement window. The incremental return upon patent approval is more likely to reflect the additional value of the patent under improved management, adjusted by the resolution of the remaining uncertainty in the granting of the patent as well as its timing.

6. Conclusion

This paper studies how, and to what extent, hedge fund activism impacts corporate innovation and contributes to the debate on the long-term impact of hedge fund activism on target firms. Although target firms’ R&D expenditures drop in the five years following hedge fund intervention, patent quantity and quality actually improve, suggesting that target firms’ innovation becomes more efficient. We analyze several plausible mechanisms for the improvement, including refocusing the firm’s efforts towards its core expertise; more efficient reallocation of innovative resources (patents and innovators), and better aligned incentives. Finally, we show that the link between hedge fund interventions and innovation efficiency seems at least partially driven by the effort of the activists rather than their selection abilities.

[25] See Lerner and Seru (2017) for a detailed discussion on the patenting process at the USPTO.

[26] Results are robust if we tighten up the sample to patents filed during [t−36, t−24] months so that their expected grant dates are around the intervention date.

Appendix A. Variable definition and description

Variable	Definition and description
	a. Innovation variables
R&D expense	Research and development expenses (XRD).
R&D ratio	Research and development expenses (XRD) scaled by total assets (AT).
New patents	Number of patent applications filed by a firm in a given year.
Average citations	Average number of lifetime citations received by the patents applied for by a firm in a given year.
Originality	One minus the Herfindahl Index of the number of cited patents across 2-digit technological classes defined by the NBER patent database.
Generality	One minus the Herfindahl Index of the number of patents across 2-digit technological classes which cite the specific patents.
Explorative	Percentage of explorative patents filed in a given year by the firm; a patent is explorative if at least 80% of its citations do not refer to existing knowledge, which includes all the patents that the firm invented and all the patents that were cited by the firm's patents filed over the past five years.
Exploitative	Percentage of exploitative patents filed in a given year by the firm; a patent is exploitative if at least 80% of its citations refer to existing knowledge, which includes all the patents that the firm invented and all the patents that were cited by the firm's patents filed over the past five years.
Diversity	One minus the Herfindahl Index of the number of patents filed by a firm in the past across 2-digit technological classes defined by the NBER patent database.
Distance (Patent to firm)	See Table 5. Please refer to Akcigit, Celik, and Greenwood (2016) for a detailed discussion of this measure.
	b. Innovative resource reallocation
Inventor leavers	An inventor is a leaver of firm i in year t if she generates at least one patent in firm i between [t-3,t-1] and generates at least one patent in a different firm between [t+1,t+3]; identified from Harvard Business School patenting database.
Inventor new hires	An inventor is a new hire of firm i in year t if she generates at least one patent in another firm between [t-3,t-1] and generate at least one patent in firm i between [t+1,t+3]; identified from Harvard Business School patenting database.
Patent sell	Number of patents sold by a firm. Identified from Google Patent Transactions Database compiled by USPTO.
Patent buy	Number of patents bought by a firm. Identified from Google Patent Transactions Database compiled by USPTO.
	c. Firm characteristics
Age	Number of years since IPO, as reported in Compustat.
Total assets	Total assets (AT).
MV	Market value of the firm is defined as common shares outstanding (CSHO) times the share price.
ROA	Earnings before interest, taxes, depreciation, and amortization (OIBDP) scaled by lagged total assets (AT).
M/B	The market value of the firm, defined as the sum of the market value of common equity, the debt in current liabilities (DLC), long-term debt (DLTT), preferred stock liquidating value (PSTKL), and deferred taxes and investment tax (TXDITC), scaled by the book value of the firm (AT).
Leverage	Book debt value (sum of debt in current liabilities (DLC) and long-term debt (DLTT)) scaled by total assets (AT).

Appendix B. Additional considerations involving the patent data

This appendix is structured following the checklist approach advocated by Lerner and Seru (2017) (see their Table 10). Lerner and Seru (2017) suggest that researchers using patent data confirm that their analyses address the following questions.

1. To what extent are the key policy changes occurring around times when patenting and citations per patent accelerated?
   This feature of the data has a limited influence on the analyses in our setting since the activism events are staggered over the sample period and time trends are controlled by both the propensity-score-matching algorithm and the year fixed effects. We also show in the Online Appendix that the results presented in Section 3 continue to hold when we repeat the analysis using activism events that occurred over the first part of our sample period, 1994—2002.
2. Are firms in industries that experienced a surge of patenting or in citations per patent (e.g., computers and electronics) included in one of the sub-populations being analyzed?
   This concern is clearly important and that is why we implement the propensity matching within each industry. Our results are also robust when we study specific industries, as reported in Section 3 and Table 3, Panel B.
3. To what extent are firms in states that experienced a surge of patenting or citations per patent (e.g., California and Massachusetts) included in one of the sub-populations being analyzed?
   This concern does not apply to the analysis in this paper although, as pointed out above, we control for industry affiliation directly in our propensity-score-matching.
4. Are firms with features akin to those that experienced a surge in patenting or citations per patent (e.g., those with a high market-to-book value) included in one of the sub-populations being analyzed?
   Controlling for firm characteristics that are correlated with patenting activities is an important factor that we take into consideration by implementing the propensity-score-matching using firm size (logarithm of assets), market-to-book ratio, and return on assets (ROA) measured at t-1, as well as the change

in the target firm ROA measured between years *t*-3 and *t*-1 so as to capture pre-event trends of deterioration in the operating performance of target firms. As we report in the text, our results are both qualitatively and quantitatively similar when we add more firm characteristics to the calculation of propensity scores.

5. To what extent are the patterns seen consistent across the sample (e.g., across the entire period under study), or do they vary in ways that might be associated with unobserved factors that may be driving patenting practice? Are the coefficients of the effect consistent across the sample, or being driven by a sub-group?
   As we report in the text, our results are robust to different time periods and different industries categorized by their innovation input-output lag. The Online Appendix provides two additional robustness checks. First, we restrict the definition of "innovative" target firms to those that have at least five patents prior to the year of the intervention and find qualitatively similar evidence. Second, we adopt a negative binomial specification instead of that in Eq. (1), including year and firm fixed effects, and find similar results.
6. May the results be driven by selection biases, due to the researchers' inability to observe pending patents or not-yet cited patents? Are the results robust to treat these truncation biases in different ways?
   This is an important issue to consider. We correct for truncation using the correcting factor proposed in Hall, Jaffe, and Trajtenberg (2001). We also confirm that the results are robust in the first subsample, 1994—2002, which is less likely to be influenced by this truncation problem.
7. Could the results be driven by the exit of firms, and the likelihood that some or all of the patents pending at the time of exit will not be assigned to this firm, but rather to a successor entity? To what extent may this exit truncation problem be linked to the phenomenon under study?
   We compare the exit behavior of the real target firms and the propensity-score-matched firms in Table A15 of the Online Appendix and observe no difference in the target and matched control firm exit behavior.
8. Is there any way to ascertain the extent to which the firms under study may be engaging in misleading assignment practices, in order to disguise their technological strategy from competitors?
   As we report in the text, target firms are matched to controls based on several pre-event firm characteristics that drive targeting. There is no reason to expect that deceptive patent assignment practices would differ systematically across target and control firms.
9. To what extent may the limitations of the concordances between patent assignees and firms be systematically affecting the results of the analysis (a consideration particularly relevant when the implications of the market for corporate control on innovation are being studied)?
   We adopt the dynamic concordance between USPTO assignees and public firms, which controls for this constraint to some extent. This issue is particularly important in the analysis regarding patent transactions (re-assignments), as discussed in Online Appendix 3. In that analysis we make sure the re-assignments are not capturing the reallocation of IP within a firm (between different divisions) by directly analyzing their division names.
10. Do the citation practices of the firms under study differ significantly from the norm, which might suggest that firms are engaging in strategic use of citations?
   This concern is particularly important when patent citation records are used as a proxy of information and knowledge flows from one innovator to another. This paper does not utilize patent data in this manner. One related implication of this concern is that firms might strategically cite their own patents, and we attempt to mitigate this concern by removing all self-citations made by target and control firms.

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