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Shareholder Power and Corporate Innovation: Evidence from Hedge Fund Activism

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Abstract

This paper studies how hedge fund activism reshapes corporate innovation. Firms targeted by hedge fund activists experience an improvement in innovation efficiency during the five-year period following the intervention. Despite a tightening in R&D expenditures, target firms experience increases in innovation output, measured by both patent counts and citations, with stronger effects seen among firms with more diversified innovation portfolios. We also find that the reallocation of innovative resources and the redeployment of human capital contribute to the refocusing of the scope of innovation and lead to gains in efficiency. Finally, we show that improvement in innovation efficiency is a by-product of asset reallocations triggered by activist interventions at the target firms.

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1. Introduction

Since the rise of shareholder rights in the 1980s, there has been an ongoing debate among academics, practitioners, and policy makers 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. Most importantly, the concern that stock market pressure causes "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 come to epitomize the movement for stronger shareholder rights and empowerment. The concern has reached a heightened level in 2015 when Laurence Fink, the chairman and CEO of BlackRock, the world's largest institutional investor, voiced his concern about the short-term oriented pressure on management from the stock market, and singled out activist investors as an important source for such a pressure.[1]

[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

Between 1994 and 2007, there were more than 2,000 engagements by hedge fund activists in which hedge funds acquired significant, but strictly minority, equity stakes (typically 5-10%) in companies that they perceived to be undervalued, and then proposed changes to payout policies, business strategies, and corporate governance, often publicly and aggressively.[2] Recent studies, covering both the U.S. and international markets, have documented that the target firm's stock price increases by a range of 5-10% when the market first learns of the activist's intervention. Moreover, the interventions are not followed by a decline in either stock returns or operating performance during the five-year window after the initial short-term gain.[3] 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, opponents of hedge fund activism have resorted to a "myopic activists" view, claiming that activists' agendas are biased towards the pursuit of short-term stock gains at the expense of firms' long-term values.[4]

Corporate innovation is a crucial component in the debate on the consequences of hedge fund activism. This is because innovation is the most important engine for economic growth, but is also arguably the most susceptible to short-termism.[5] Hedge fund activism may have a direct impact on corporate innovation because the activists increasingly target technology companies,[6] however, the indirect effect is likely to be more widespread as a by-product of changes in corporate financial and business strategies. For example, companies targeted by activist hedge funds tend to increase shareholder payouts (and hence decrease the funds available for discretionary spending) and to reduce overall

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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] We refer the readers to the reviews by Brav, Jiang, and Kim (2010, 2015) for general information about hedge fund activism.

[3] See Brav, Jiang, Partnoy, and Thomas (2008), Clifford (2008), Klein and Zur (2009), Greenwood and Schor (2009), and Krishnan, Partnoy and Thomas (2015) for U.S. companies; and Becht, Franks, Mayer, and Rossi (2009), Becht, Franks, Grant and Wagner (2015) for non-U.S. markets.

[4] See Bebchuk, Brav, and Jiang (2015) and Coffee and Palia (2015) for detailed discussions regarding the debate.

[5] In the same letter as referenced in Footnote 1, Fink then 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."

[6] 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. Url: http://blogs.law.harvard.edu/corpgov/2012/04/17/hedge-fund-activism-in-technology-and-life-science-companies/.

investment. Since R&D activities require significant and often contingent investment and take a long time to deliver highly uncertain returns, these investments could be directly or indirectly targeted for reduction or reallocation.

Neither the direction nor the magnitude of activists' impact on overall innovative activities is clear *a priori*. First, activists might have a negative impact on innovation because, as Holmstrom (1989) has argued, innovative activities involve the exploration of untested and unknown approaches that have a high probability of failure, and the innovation process involves contingencies that are impossible to foresee. Given the lack of observability and predictability, the concern is that management might respond to pressure from current shareholders by adopting investment/innovation policies that are detrimental to long-term firm value. More powerful current shareholders could lead to greater misalignment. Such a concern is exemplified in the recent hostile intervention by Trian Partners, a major activist investor, at DuPont, an R&D powerhouse.[7] This argument, however, rests on the premise that there is a disconnect between the stock price and firm value when these long-term projects are undertaken, or that investors as a whole fail to properly value innovation. Recent work by Hirshleifer, Hsu, and Li (2013) and Cohen, Diether, and Malloy (2013) offers support for this argument by showing that in a cross section the stock market fails to incorporate information on past success when valuing innovation. However, there has been no clear evidence that investors systematically undervalue innovation and, in fact, opposite predictions may also arise from equilibrium models (Pastor and Veronesi (2009)).

Second, although managerial preferences and objectives may not be entirely 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 are positive NPV in expectation, and agency problems may lead to both over- and under-investment. For example, over-investment may arise if specialized investment entrenches the management (Scharfstein and Stein (2002)) or if managers derive

[7] See, "DuPont's R&D Is at Center of Fight With Activist," *The Wall Street Journal*, Oct 27, 2014. In early 2015, Trian proposed that DuPont consider splitting its agriculture, nutrition and health, and industrial biosciences divisions from its materials businesses. Tom Connelly, DuPont's chief innovation officer, states in the article that, "We are the go-to people because we have innovation capabilities," and that "Our relevance increases as the breadth of our offering does increase." Trian's view regarding the extent of successful innovation at DuPont is that "If the strategy was really working, it should have manifested itself by now in superior economic performance on the income statement, and it hasn't," says Ed Garden, chief investment officer at Trian.

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 R&D than what management wants if diversified investors have more capacity to absorb innovation risk (Aghion, Van Reenen, and Zingales (2013)).

This paper contributes to this debate by providing direct and comprehensive evidence on the effect of shareholder power, in the form of hedge fund activism, on firm innovation. 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 the 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 innovation output— measured by patent counts, citation counts per patent, patent generality, and patent originality—after the intervention, and most of these measures actually improve significantly. The improvement in innovation is not uniform across target firms. It is driven by firms that prior to the intervention had a diverse portfolio of patents but after the arrival of activists choose to refocus, leading to an increase both in patents and more citations per patent. Moreover, the increase in innovation is concentrated in technological areas that are central to the core capabilities of the target firms. This set of results constitutes preliminary evidence that firms tend to improve innovation efficiency in the period following the intervention.

Next, we explore two mechanisms through which hedge fund activism impacts targeted firms' innovation efficiency. First, hedge fund intervention is followed by a more active and efficient reallocation of outputs from innovation. Specifically, target firms transact (sell and buy) an abnormally high number of existing patents compared to their matched peer and patents sold are less related to their technology expertise. Interestingly, patents sold post hedge fund intervention receive a significantly higher number of citations relative to their own history or to their matched peers (patents in the same technology class with similar vintage). This pattern does not appear prior to intervention, or among patents sold by non-targeted firms, suggesting that matching patents to new and better-suited owners contributes to the observed efficiency gain following the hedge fund intervention.

The second mechanism involves the redeployment of innovators as target firms engage in a more active reallocation of inventors 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 companies and those that are hired anew. 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, these changes constitute a positive outcome due to the reshuffling of human capital where the key innovative personnel are matched or re-matched to work environments where they can be more productive.

The link we uncover between hedge fund activism and a more efficient reallocation of innovation assets is intriguing in light of the fact that R&D or general innovative activities are usually not the primary stated objectives stated by activist hedge funds.[8] Similarly, activists rarely possess the precise in-depth scientific knowledge that is required to guide the innovative process. We therefore attempt to explore the channel linking activists' actions and the changes in innovative output described above. Building on previous research (Greenwood and Schor (2009); Brav, Jiang, and Kim (2015b)) showing that hedge funds facilitate asset reallocation by spinning off assets, segments, or even selling the whole firm, we conjecture that patent transactions and innovator turnover may be a byproduct of this broader asset redeployment. Consistent with this redeployment-driven channel, we show that asset divestures triggered by hedge fund activism are indeed accompanied by an abnormal number of departing inventors as well as patent sales.

Our study presents a more nuanced picture than a straight answer as to whether hedge fund activism, or pressure from the stock market in general, encourages or impedes corporate innovation. While inputs

[8] There are exceptions, for example, Starboard Value LP is known for targeting intellectual property-rich firms with explicit demands regarding the firms' R&D and patenting policies. In addition, in recent years hedge funds have more frequently supported changes in targets' R&D activities. Such cases include Trian Partners' intervention at DuPont and Third Point's at Amgen in 2015.

to innovation, measured by R&D expenditures, decline post hedge fund intervention (which reflects the broader decline in the size of the target firm), the outputs from innovation, measured by patent quality and quantity, tend to improve. These improvements tend to concentrate in areas that are central to the firms' business and technological expertise. Thus, our evidence suggests that firms become "leaner" but not "weaker" on the innovative front. Moreover, the efficiency gains emanate also from the extensive margin through the redeployment of innovative assets (patents or innovators). Such a pattern parallels -- and may well be a byproduct of – 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, Jiang, and Kim (2013)). This offers an explanation as to why the positive stock market reaction to announced hedge fund activism is highest when activists propose the restructuring of major assets, such as a sale of a specific asset, a spin-off of a segment, or even a sale of the whole firm (Brav, Jiang, Partnoy, and Thomas (2008); Greenwood and Schor (2009)).

Our study contributes to the growing literature exploring how financial markets and corporate governance affect corporate innovation. A list of factors includes: Firms' going public decisions (Bernstein (2014)), anti-takeover provisions (Chemmanur and Tian (2013)), institutional ownership (Aghion, Van Reenen, and Zingales (2013)), stock market liquidity (Fang, Tian, and Tice (2014)), and labor unions (Bradley, Kim, and Tian (2013)). Our study relates innovation to an increasingly important new form of market-based corporate governance, namely, shareholder empowerment represented by hedge fund activism, with the goal to inform the current debate as to whether the pressure from the stock market impacts the long-term viability of target companies.

Closest to our paper is recent work by Seru (2013), who argues that firm boundaries matter for innovation by showing that firms acquired in diversifying mergers produce fewer and less novel patents after such activities and that this is driven by a decline in inventors' productivity after the merger rather than inventor exits. Our study is consistent with Seru (2013) since we show that the redrawing of the target firm's boundaries, by refocusing on the firm's technological expertise, leads to higher innovative efficiency, except that the target firm's boundaries are reshaped by the activists rather than via a control change. Our paper is also related to recent work on the effect of private equity/venture capital involvement with innovation (Lerner, Sorensen, and Stromberg (2011), Chemmanur, Loutskina, and Tian (2014)). Activist hedge funds are, however, critically different from PE/VC in that their primary role is not financing, but rather 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 target firms in different stages of their life cycle.

2. Data and Sample Overview

2.1 Data sources

2.1.1 Innovation

We adopt two sets of measures to capture both the inputs to and the output from the innovation process. The input measure is the level of annual R&D expenditures from Compustat. While this measure is simple and intuitive, the use of R&D suffers from several limitations: it is incomplete (more than 50% of the observations are 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)).[9]

The second measure, proxing for output from innovation, is a firm's patenting activity, reflecting the successful use of innovation inputs, both observable and unobservable. The use of patenting activity has become a standard practice in the literature (e.g., Acharya and Subramanian (2009); Aghion, Van Reenen, and Zingales, (2013); Seru (2013)). We access the NBER patent database as of 2013 to obtain annual patent-level information from 1991 to 2006. The relevant information includes information on the patent assignee (the entity, such as the firm, which owns the patent), the number of citations received by the

[9] We winsorize firms' financial data at the 1% extremes. 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.

patent, the technology class of the patent, and the patent's application and grant year. Bhaven Sampat's USPTO patent and citation data allows us to extend the NBER patent database up to 2010.[10]

While the use of the NBER patent database facilitates the measurement of general patenting activities, we are also interested in data that would allow us to measure 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.[11] Covering the period from 1991 to 2010, this database provides the names of the inventors (i.e., the individuals who receive credit for producing a patent) and their affiliation with the assignees, thus tracking the mobility of individual inventors (see Lai, et al. (2013) for details).

We obtain information on patent transactions from Google Patent, which, through a special arrangement with the USPTO, gathers details on patent transactions from 1991 to 2010.[12] This database provides necessary information for analyzing patent mobility: the name of the patent buyers (assignees), the name of the patent sellers (assignors), the unique patent identifiers (patent numbers), and the patents' transaction dates (the dates on which re-assignments were recorded at the patent office). The merge of Google Patent and the NBER database proceeds in three steps. First, a standard spelling distance algorithm matches assignee names to possible company names (see Kogan, et al. (2013)).[13] Second, we filter the matched results and manually resolve unmatched assignors and assignees whenever possible. Finally, we follow Serrano (2010) and Akcigit, Celik, and Greenwood (2013) to drop the assignments that do not appear to be associated with an actual patent transaction. Such examples include name changes and corrections. Finally, we exclude patent transactions that occur entirely within the same firm, such as assignments representing transactions between employees (inventors) and their employers (assignees).

[10] Available at: http://thedata.harvard.edu/dvn/dv/boffindata.
[11] Available at: http://dvn.iq.harvard.edu/dvn/dv/patent.
[12] The data are accessible via bulk downloading of text files. See http://www.google.com/googlebooks/uspto-patents.html.
[13] The algorithm is based on code provided by Jim Bessen, and is available at the following website: https://sites.google.com/site/patentdataproject/Home/posts/Name-matching-tool.

2.1.2 Hedge fund activism

The comprehensive sample of hedge fund activism events, covering the period from 1994-2007, is an extension of the sample studied in Brav, Jiang, Partnoy, and Thomas (2008), which describes the details of the sample selection criteria. The events are identified mainly through Schedule 13D filings submitted to the 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 any share class at mid- to large-cap companies (above $1 billion).

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, peaking in 2007, and provides some evidence of pro-cyclicality. Given the goals of this study, we limit the sample to potentially "innovative firms," defined in two ways. The first definition requires that the firm filed at least one patent in any year prior to hedge fund 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*). Table 1 Panel A indicates that about 30% of the hedge fund targets are innovative firms according to the first definition (columns 2 and 3), and that the representation drops to 24% based on the more stringent second definition (columns 4 and 5). On average, innovative target firms own about 20 patents in the year of 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.[14] The sample contains a large number of activism events in the most innovation-intensive industries, such as high tech (20% of the sample), healthcare (11% of the sample), and manufacturing (9% of the sample).

[Insert Table 1 here.]

[14] 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 *Key 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 simply measured as the number of patent applications filed by a firm in a given year that are eventually granted. The choice of application (rather than grant) year better captures the actual time of innovation (Griliches, Pakes, and Hall (1988)).

There are several frequently used measures for patent quality. Most notably, patent quality is measured using the number of subsequent citations, the patent's originality, and the patent's generality. The first, the number of citations each patent receives in subsequent years, differentiates patents based on their impact. Although there are two truncations problems with this measure, the mitigating solutions are well-recognized in the literature. The first problem arises because patents appear in the database only after they are granted, and there is a significant lag (of 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 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 does not compromise the NBER Patent and Citation database, in which 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) have developed two additional measures for 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 technology classes of patents 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.

2.2.2 Innovation strategy

Turning from patents to firms, we employ three variables to describe a firm's innovation strategy. The first variable, developed by Custódio, Ferreira, and Matos (2013), measures a firm's innovation diversity. More specifically, the 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 Almeida, Hsu, and Li (2013) and Custódio, Ferreira and Matos (2013), compares a firm's new innovations to its existing technological expertise, and summarizes the strategy by 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 considered exploratory if at least 80% of its citations are based on new knowledge. 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 relative to existing patents) or focuses on exploring new technologies.

Last, we adopt the methodology developed in Akcigit et al. (2013) to measure the distance between a given patent and firm's overall patent portfolio. Akcigit et al. (2013) first measure 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, they 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 firm owns using these technology class distance measures.[15]

2.3 Sample overview

We merge all the databases described in the previous sections to form the master database for this study. An important consideration for our analysis is the potential for a sample selection problem. We address selection by performing our main analysis on the hedge fund target firms and a control sample constructed using propensity score matching. We match each firm targeted by a hedge fund in year *t* with a non-target firm from the same year and 2-digit SIC industry that has the closest propensity score, where the propensity score for each firm is estimated using firm size (logarithm of assets), market-to-book ratio, and 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 due to deterioration in performance of target firms. Our results are both qualitatively and quantitatively similar when we add more characteristics to the calculation of propensity scores and, as will be shown later, the target and control firms are statistically indistinguishable along a number of unmatched dimensions.

Table 2 reports summary statistics (at the event year) comparing the characteristics of the hedge fund target firms with those of the matched firms. 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 innovative, in the 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 for multiple characteristics, such as size, market to book ratio, and return-on-assets, although hedge fund targets have marginally higher leverage.

Interestingly, the two samples are similar in both innovation inputs and outputs in the year of intervention despite that these characteristics are not part of the matching criteria. For example, target firms invest an equivalent of 7% of their total assets in R&D during the event year, while the same

[15] See Appendix A-2 for the detailed derivation of this measure.

number for matched firms similarly stands at 7%. 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, suggesting that event firms are slightly less innovative than their peers, but not significantly so. Similarly, target firms demonstrate slightly lower, but still similar values, for most of the variables characterizing patenting characteristics and innovation strategies, such as patent originality and generality, portfolio diversity, patenting distance, and the extent to which the overall strategy is explorative or exploitative.

[Insert Table 2 here.]

3. Hedge Fund Activism and Corporate Innovation: Overview

Our empirical analyses begin with an examination of the relation between hedge fund activism and corporate innovation. The sample consists of firm-year level observations from 1991 to 2010, where firms are limited to hedge fund targets and the matched firms that were identified using propensity score matching as described in Section 2.3. The event year for a target firm is also the "pseudo-event" year for its matched firm and we include target (matched) firm data beginning five years prior to the event year (pseudo-event year) through five years afterwards.

Our main regression adopts the standard difference-in-differences (DiD) framework:

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

In equation (1), i and t are indexed for firm and year, respectively. The dependent variable $Innovation_{i,t}$ is equal to one of the innovation input/out proxies described in Section 2.2. $I(Target_i)$ 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, and $Control_{i,t}$ is a vector of control variables, including market capitalization and firm age (both in logarithmic terms). The coefficient of interest is thus β_1, the coefficient 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 Panel A reports the results of regression (1).

[Insert Table 3 here.]

Columns (1) and (2) of Table 3 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, measured in millions of dollars. The coefficients associated with $I(Target_i) \times I(PostHFA_{i,t})$ are both negative, but are only significant in the second specification which shows 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. The finding that R&D expenditures decrease significantly even though the R&D/Assets ratio remains roughly flat is consistent with the fact that, post activism, R&D 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, Jiang, and Kim (2010, 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. Post hedge fund activism 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 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 $I(Target_i) \times I(PostHFA_{i,t})$ 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. Similarly, columns (5) and (6) show that the originality and generality of patents filed by target firms post-event also increase relative to matched firms, although only the estimate associated with originality is significant. Finally, column (7) provides additional information on the change in the number of citations per patent by focusing on the right tail of the distribution of citations. Specifically, we now constrain the previous analysis on citations to new patents to the subset of new patents that rank as the top 20% most cited patents produced by firm i in year t. The positive and significant slope on the interaction term indicates that the shift in quality documented in column (4) is accompanied by improvement at the top end of the quality spectrum as proxied by patent citations.

Figure 1 displays the changes in the output from innovation at target firms relative to that of controls by plotting the differences in pre- and post-trends in both the number of new patents and associated citations between targets and controls. The plotted coefficients, $\beta_{-3},\ldots,\beta_5$ are associated with the interactions of yearly dummies extending from three years prior to the activism event year through five years afterwards and an indicator of being targeted by hedge funds. The coefficients are estimated from the following specification in equation (2):

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

The dummy variables *d[t-3],…, d[t+5],* correspond to firm-year observations from three years before to five years after the (pseudo-) event year, and zero otherwise. $I(Target_i)$ indicate if the firm is a hedge fund target or a matched control firm. As in equation (1), the control variables include the natural logarithms of firm market capitalization and firm age and we also include firm and year fixed effects. The left panel plots the estimates of the difference between targets and controls in quantity of innovation as measured by the logarithm of the number of patents filed by firm i in year t. The right panel plots the estimates of the difference between targets and controls in quality of innovation as measured by the logarithm of the average citations received by patents filed by the firm in year t.

[Insert Figure 1 here.]

The two plots in Figure 1 show how the propensity score matching results in a negligible difference between target and control firms in the number of new patents and associated citations in the three years prior to the arrival of activist hedge funds. Divergence emerges within one to two years, and the departure in the number of patents (citations per patent) is statistically significant in the second (third) year post intervention. The length of time it takes for external monitoring to manifest in innovation activities is plausible, and is on par with the finding of Lerner, Sorensen, and Stromberg (2011). Combining the evidence on both inputs and outputs, Table 3 and Figure 1 suggest that target firms become more efficient in the process of innovation.

Some of the evidence documented so far is similar to the findings in Wang and Zhao (2014) and He, Qiu, and Tang (2014). As with the analysis in Table 3, they focus on documenting the association between hedge fund ownership and subsequent target firm innovation. However, these studies do not explore the mechanisms via which such changes take place, namely the refocusing of patenting activity, the rebalancing of the target firms' patent portfolio, and reallocation of innovators, which are the main focus of this paper.

4. Hedge Fund Activism and Innovation: Mechanisms

4.1. Hypotheses

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' technology arena, and activist proposals to reformulate the target firm's innovation are not a commonly stated goal by activists (either in the Schedule 13D filing or in accompanying news releases). The main goal of this study is thus to contribute to our understanding of the aforementioned channel, thus shedding light on the causal impact of hedge fund activists.

The body of literature on hedge fund activism, reviewed in Brav, Jiang, and Kim (2013, 2015a), has provided 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. As such, asset redeployment plays an important role in the observed improvement in operating performance. We thus hypothesize, at a general level, that the gain in innovation efficiency may be a direct by-product of the redrawing of the firm boundaries, mostly via selective asset sales and matching of unproductive assets to more suitable owners. Other changes, such as improved corporate governance and more performance-oriented incentives for management, could also impact target firms' innovation as managers are held more accountable for return on investments and firm performance.

Thus, our working hypothesis is that the general pattern observed in Table 3 is due to a shift in targets' innovation strategies in the direction of refocusing, where the reallocation of innovative assets—both patents and inventors—plays an important role. These changes occur in tandem with the overall strategic changes and, in particular, the redrawing of firm boundaries associated with hedge fund activism. Such a general strategic change should manifest itself in the various aspects of innovative activities, which we analyze in detail in the sections to follow.

4.2. Cross-sectional heterogeneity: Diversity of innovation

Applying the literature on the scope of operation and the value of the firm (see the survey by Stein (2003)) to the innovation space, some recent studies have analyzed the effect of diversity on innovation. For example, Seru (2013) shows that target firms in diversifying mergers produce fewer and less novel patents after such mergers, but that firms overcome this difficulty by managing innovation using strategic alliances and joint ventures to increase innovation in areas that are outside the firm's core expertise. In a related setting, Bena and Li (2014) show that firms are more likely to acquire technologically similar targets and this type of merger is associated with larger benefits due to synergies.

Our test is motivated by Akcigit et al. (2013) 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. Given that one important theme of hedge fund activists is the change in strategic operations, we expect that firms which, at the outset, had a more diverse portfolio of innovation will benefit more from the refocusing brought about by activists. An empirical assessment of such cross-sectional heterogeneity requires that we re-run equation (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 now becomes:

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

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.

[Insert Table 4 here.]

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 subsamples. More important is that β_1 is 0.211, about 3 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)), but the difference is not significant. The message from Panel A is that target firms which, prior to the intervention, had a diverse set of patents generate more patents and more citations per patents within the five-year window after the arrival of activists. This evidence is interesting in light of a fact shown later (Section 4.3) that intervention is associated with the selling of patents that are distant from the target firms' main technological expertise.

Panel B presents further evidence that the increase in patents and citations is entirely 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 defined as key, or central to a firm, if at least 20% of the firm's patent stock is in 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 central to a firm. In columns (5) and (6), the dependent variables are constructed by counting the number and average citations of the new patents not in the firm's central technology class. As can be 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 (0.162 and 0.151 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 evidence so far suggests that the change in innovative activities originates from target firms with a diverse set of patents, which, after the arrival of activists, focus their innovative activities on their core technological expertise. But do these changes simply reflect efforts to innovate in well-trodden areas that the target has innovated in the past? Alternatively, are these genuine attempts to create new patents that move beyond the past innovations while remaining within the same technological class? To address this set of questions we 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 classified as explorative if at least 80% of its citations refer to new knowledge (all the patents that the firm did not invent and all the patents that were 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 constructed for patents from the central technology class (column 3) or new patents not from the central technology class (column 7). We separately 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, 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. 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 3.3% (column (3), significant at the 5% level) post intervention. Changes in exploitative patents in the key classes and changes in both types of patents in the non-key classes are all far from being significant.

Overall, this evidence is consistent with the view that post-intervention the improvement in innovation productivity is more pronounced among firms who started with a more dispersed innovation portfolio but then refocus their innovative activities within the core technological capabilities while seeking to move away from knowledge that they have generated in the past. We now turn to the more precise examination of the characteristics of patents that get reallocated and whether these patents are put to better use once they has been sold by the target firms.

4.3. Reallocation of patents

4.3.1. Example of intervention seeking the reallocation of patents: Starboard Value and AOL, Inc.

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

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

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

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

Soon thereafter, AOL retained Evercore Partners as its financial adviser, and, in early April 2012, the company announced that it would sell more than 800 patents and related patent applications to Microsoft for $1.06 billion. The company agreed to grant Microsoft a non-exclusive license to the more than 300 patents and patent applications the company chose to retain. The agreement was reached after an open auction with multiple bids by interested companies. AOL share prices increased roughly 40% over the three months following the sale of the patents.[16]

4.3.2. Transaction of patents and subsequent performance

Motivated by the case described above and our previous analyses, this section proceeds to study the reallocation of patents owned by target firms (and their matched firms) through patent transactions, particularly the sale of patents, and the resulting changes in patent portfolios and innovation efficiency. We start with the same specification as in equation (1), but we replace the dependent variable with patent transactions, that is, the annual number of patents purchased (sold) by a firm, scaled by the total number of patents owned by the firm in that year. The construction of the dependent variable necessarily constrains the relevant sample to firm-year observations where firms own at least one patent during the event year. We include year fixed effects in all specifications and either industry or firm fixed effects. Results are reported in Panel A of Table 5.

[Insert Table 5 here.]

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

The coefficient on the interaction term, $I(Target_i)\times I(Post_{i,t})$, in columns (1) and (2) of Panel A reveals that firms increase the number of patent sales post intervention at an annual rate of approximately 0.55%, as compared to the unconditional annual sale rate of 0.8%. As to patent purchases, the same coefficient in column (3) is insignificant with industry fixed effects but is statistically significant once we include firm fixed effects (column (4)). The question that naturally follows is, then, which characteristics of patents, especially with regard to their relation to the core competence of the firms, 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 is a dummy variable set to one if a patent sale occurred in a given year, $I(PatentSale_{j,i,t})$. The key independent variable is $Distance_{j,i,t}$, which follows the methodology developed in Akcigit et al. (2013) to measure 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 $Distance_{j,i,t}$. The Appendix contains a more detailed description of the variables and the parameter. $Before_{i,t}$ 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 belonging to the matched firms. All specifications include annual and patent vintage fixed effects. We opt for the linear probability model in order to accommodate high-dimensional fixed effects.

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. (2013), the positive estimate on $Distance_{j,i,t}$ indicates that firms are more likely to sell a patent that is distant from the firm's portfolio. Importantly, this effect is weaker for target firms pre intervention, where 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, where the coefficient on $Distance_{j,i,t} \times After_{i,t}$ is positive and significant at 5% or 10% levels in all specifications.

In sum, hedge funds 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 the target firm innovation. We next ask whether the sale of patents also represents efficient reallocation of innovation resources to the buyers, in addition to the sellers.

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 citations around patent transactions and to compare the difference between targets and non-targets. The regression specification is as follows:

$$Citation_{j,t} = \sum_{k=-3}^{+3} \beta_k \, d\left[t+k\right]_{j,t} + \gamma \cdot Control_{j,t} + \alpha_j + \alpha_t + \varepsilon_{i,t} \qquad (4)$$

In equation (4), the dependent variable is the number of new citations an existing patent *j* receives in year *t*. The key independent variables, $d\left[t+k\right]_{j,t}, k = -3, \ldots, +3$, are dummy variables for observations that are *k* years from the event year, where an event is the sale of a patent by a target firm if the sale occurs within two years post intervention, or that by a non-target firm if the sale occurs within two years post the pseudo-event year. The control variable is patent age (in logarithm). The regression incorporates year and patent (or technology class) fixed effects to absorb time- and patent-specific unobservable characteristics, and we cluster standard errors at the patent level. The odd (even) numbered columns of Panel C of Table 5 report the regressions for target (non-target) firms.

The three sets of coefficients on $d\left[t+k\right]_{j,t}, k = -3, \ldots, +3$ for target firms (in columns (1), (3), and (5)) exhibit a "V" shape pattern centered on the year of sale. Focusing on columns (5) and (6), in which we include patent fixed effects, we see that three years before the sale, the impact of patents eventually sold post hedge fund activism is statistically equivalent to their own long run average, but then experiences a significant deterioration in the next three years (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 management of new owners. In fact, annual citations of target firms' patents that are sold are significantly higher than the levels in the year of sale (as evidenced by the significant *F*-statistics testing the difference *d[t] – d[t-3]*).

In contrast, columns (2), (4), and (6) of Table 5 Panel C, in which we follow patent sales at non-target firms, show an opposite pattern: Citations to patents that will be sold see slight decline prior to the sale, that is, *d[t] – d[t-3]* is small and insignificant. Post sale, the number of citations for these patents increases, although the magnitude of the change, *d[t+3] – d[t],* is substantially smaller than the change in the number of citations for patents sold by target firms for the same time period. With the inclusion of patent fixed effects in column (6) we actually see no change in citations to sold patents in the three years post-sale. 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.

[Insert Figure 2 here.]

A plot of the coefficients $d\left[t+k\right]_{j,t}, k = -3,\ldots, +3$ for both groups of firms in Figure 2 provides a visualization of the dynamics of citation counts. While the sale of patents by all firms is preceded by a decline in citation count, the improvement is evident only for the targets of hedge fund activists. The joint pattern echoes the finding in Brav, Jiang, and Kim (2015b), who find that physical asset (plant) sales post hedge fund intervention exhibit better ex-post performance than plant sales under other circumstances. This evidence is consistent with the idea that activism triggers the reallocation of assets and "improved matching" of assets to new owners.

4.4. 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 (2013); Bernstein (2014)).

Following Bernstein (2014), we rely on 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 finally, 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.[17]

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 equation (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 6 Panel A.

The insignificant coefficients on *I(Target)* indicate that the unconditional rate of innovator departures and arrivals at target firms is similar to that of the 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 5% levels) relative to the control firms by 6.2% (8.6%) in the specification with firm fixed effects.

[Insert Table 6 here.]

Next, we attempt to 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 equation (1) except that the dependent variable is now the change, from the period [t-3, t-1] to [t+1, t+3], in the number of new patents (the first three columns of Table 6 Panel B) or new citations per

[17] Bernstein (2014) 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.

patent (the last three columns). For each dependent variable, the three columns cover the three groups of inventors. 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 a selection effect (i.e., the less productive inventors leave the firms, raising the average of the remainder) or a treatment effect (i.e., the stayers have access to more resources and/or managerial support after the reduction), both of which reflect favorably on the retention of innovators post hedge fund intervention.

Parallel to the ex post performance of sold patents, the "leavers" also fare better at their new employers although these effects are significantly weaker: the increase in their new patents is positive but insignificant (column (2)) and the impact of their new patents is only marginally significantly higher than their peers (column (5)). More specifically, inventors who have departed immediately after hedge fund intervention later produce patents that receive about three citations per piece more than inventors in the control sample, suggesting that these individuals were able to land on "greener pastures." These results, although striking, do not allow us to conclude that a similar improvement would not have occurred had the "leavers" remained as "stayers." However, if this were indeed the case, then the coefficient of $I(Target_i) \times I(Post_{i,t})$ would be under-estimated for "stayers" because the departure induces an unusual negative survivorship bias (i.e., the better inventors leave). 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.

5. Causal Inferences: Linking the Reallocation of Innovative Resources to Activism-Triggered Reallocation of Assets

The analyses thus far have shown that hedge fund activism is associated with an overall reorganization in which target firms reallocate underutilized assets and these innovative resources (patents and inventors) match to better-suited owners and employers. The consistency of results from different angles and setups makes it unlikely that an alternative economic channel drives all these findings. Nevertheless, one exception might be that activists, being informed and sophisticated investors, are able to target firms whose general business strategies—which include innovative strategies—were about to go through voluntary changes in the same direction.

It is worth noting that current literature (notably Brav, Jiang, Partnoy, and Thomas (2008), Klein and Zur (2009), Gantchev (2013) and Brav, Jiang, and Hyunseob (2015b)) has refuted the hypothesis that the changes would have been undertaken voluntarily because launching an intervention incurs a significant cost beyond that associated with acquiring a block of shares, and because both stock returns and operating performance are significantly positive for "hostile" cases where management openly resisted the changes advocated by the activists. In addition, there is a significant incremental change in firm performance when blockholders change from a passive to an activist stance, which is also consistent with the view that the activist exerts the costly effort only because such effort should, in expectation, causes the subsequent changes in performance.[18]

Activists do not usually explicitly state an intention to restructure the process of innovation at target firms. Moreover, most activists do not possess the specific scientific knowledge or technological expertise that is required to guide the innovative process. Building on the cumulative evidence in the existing literature that hedge funds often trigger asset reallocations via divestitures, spin-offs, and the sale of the whole firms (see a summary in Brav, Jiang, and Kim (2015b)), we therefore attempt to trace a channel from asset reallocation to patent and human capital redeployment as the latter could be a natural by-product of the former. Thus, if the redeployment of innovative resources can be shown to accompany asset reallocation post intervention, then it is reasonable to infer that the same intervention also has a causal impact on the changes in innovative activities and policies.

To this end, we merge our patent and inventor data with data on divestitures (*Divestiture*) from the Thomson Reuters SDC Platinum. We define *Divestiture* as a divestment or an asset sale of at least 10%

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[18] In the recent Trian vs. DuPont case (see footnote 7), Trian Partners spent roughly $8 million to launch a proxy battle against DuPont in May 2015, over two years after the initial investment in the target company. It is implausible that changes, which include director turnover, a $5 billion share buyback, a major cost cutting initiative, and a spin off (Chemours), would have happened absent the activist's advocacy and insistence.

of the total assets of a target firm. Panel A of Table 7 lists the time series of divestitures at target firms from 1994 to 2007. It shows that around 30% of all the target firms complete at least one asset divestiture, and the number is even higher for innovative firms.

[Insert Table 7 here.]

We estimate the following specification, with all event-level observations in one cross-section, allows us to link the reallocation of innovative assets to divestitures:

$$\ln(1 + \#leavers_{i,t} \; / \; \#\, patents\ sold_{i,t}) = \beta Divestiture_{i,t} + \gamma Control_{i,t} + \alpha_{SIC3} + \alpha_t + \varepsilon_{i,t} \tag{5}$$

In equation (5), the dependent variables are the number of patents sold by the firm or the logarithm of the number of inventors who leave the firm (the "leavers"), both measured as the total number in the three years post intervention. The key independent variable is the divesture dummy that equals one if a divesture event occurs within two years post intervention. Controls include the logarithms of firm size and age. Finally, both regressions include year and industry fixed effects. The results are reported in Panel B of Table 7.

Consistent with the hypothesized positive association between divestitures, patent sales, and human capital redeployment, we find that the coefficients associated with the *Divestiture* dummy are positive and significant in both columns, suggesting that the reallocation of assets also triggers the reallocation of innovative resources. The economic effect is also sizable. For example, a divesture is associated with a 36.5% increase in the number of patents sold, and a roughly 10.6% increase in the number of leavers. Similar to the earlier findings regarding physical assets, we find that hedge fund activism is associated with the divestiture of underperforming and peripheral innovative assets, the improved of productivity of innovative assets retained, and the revival of the divested innovative assets in the hands of new owners/employers.

6. Conclusion

In this paper, we study how and to what extent hedge fund activism impacts corporate innovation. We find that target firms' R&D expenditures drop in the three years following hedge fund intervention. Yet, target firms' innovation output, as measured by patent quantity and quality, actually improves even though R&D expenditures have remained constant or even decreased, suggesting that targets become more efficient in their innovation process. We identify two plausible mechanisms through which hedge fund activists improve target firms' innovation efficiency. First, hedge fund activists are able to better reallocate innovative resources. Patents sold by target firms within three years post hedge fund intervention receive significantly more citations relative to their matched peers, reversing a pattern of declining citations prior to the intervention. Second, the structural changes associated with the entry of activists leads to the redeployment of human capital, which is crucial to the innovation process. Inventors retained by target firms are more productive than those at non-target firms, and inventors who leave following hedge fund intervention become more productive with their new employers. Finally, we show that the link between hedge fund interventions and improvements in innovation efficiency seems to be a byproduct of broader asset reallocation triggered by activism.

References

Acharya, Viral, and Krishnamurthy Subramanian, 2009, Bankruptcy codes and innovation, *Review of Financial Studies* 22, 4949–4988.

Aghion, Philippe, John Van Reenen, and Luigi Zingales, 2013, Innovation and institutional ownership, *American Economic Review* 103, 277–304.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood, 2013, Buy, keep or sell: Economic growth and the market for ideas, Working paper, No. 19763, National Bureau of Economic Research.

Almeida, Heitor, Po-Hsuan Hsu, and Dongmei Li, 2013, Less is more: Financial constraints and innovative efficiency, Working paper, University of Illinois.

Bebchuk, Lucian, Alon Brav, and Wei Jiang, 2015, The long-term effects of hedge fund activism, *Columbia Law Review*, forthcoming

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

Becht, Marco, Julian Franks, Jeremy Grant and Hannes Wagner, 2015, The Returns to Hedge fund Activism: An International Study, Working paper No. 402/2014, ECGI Finance.

Bena, Jan, and Kai Li, 2014, Corporate innovations and mergers and acquisitions, *Journal of Finance* 69, 1923–1960.

Bernstein, Shai, 2014, Does going public affect innovation? *Journal of Finance*, forthcoming.

Bradley, Daniel, Incheol Kim, and Xuan Tian, 2013, The causal effect of labor unions on innovation, Working paper, Indiana University.

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

Brav, Alon, Wei Jiang, and Hyunseob Kim, 2010, Hedge fund activism: A review, *Foundations and Trends in Finance* 4, 185–124.

Brav, Alon, Wei Jiang, and Hyunseob Kim, 2015a, Recent advances in research on hedge fund activism: Value creation and identification, *Annual Review of Financial Economics*, forthcoming.

Brav, Alon, Wei Jiang, and Hyunseob Kim, 2015b, The real effects of hedge fund activism: Productivity, asset allocation, and labor outcomes, *Review of Financial Studies,* forthcoming.

Chemmanur, Thomas, and Xuan Tian, 2013, Anti-takeover provisions, innovation, and firm value: A regression discontinuity analysis, Working paper, Indiana University.

Chemmanur, Thomas, Elena Loutskina, and Xuan Tian, 2014, Corporate venture capital, value creation, and innovation, *Review of Financial* Studies 27, 2434–2473.

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

Coffee Jr., John C., and Darius Palia, 2015, The impact of hedge fund activism: Evidence and implications, Columbia Law and Economics Working Paper No. 489.

Cohen, Lauren, Karl Diether, and Christopher Malloy, 2013, Misvaluing innovation, *Review of Financial Studies* 26, 635–666.

Custódio, Cláudia, Miguel A. Ferreira, and Pedro Matos, 2013, Do general managerial skills spur innovation? Working paper No. 376, ECGI Finance.

Fang, Vivian, Xuan Tian, and Sheri Tice, 2014, Does stock liquidity enhance or impede firm innovation? *Journal of Finance* 69, 2085–2125.

Gantchev, Nickolay, 2013, The costs of shareholder activism: Evidence from a sequential decision model, *Journal of Financial Economics* 107, 610–31.

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

Griliches, Zvi, Ariel Pakes, and Bronwyn H. Hall, 1988, The value of patents as indicators of inventive activity, Working paper No. 2083, National Bureau of Economic Research.

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, 2001, The NBER patent citation data file: Lessons, insights and methodological tools, Working paper No. 8498, National Bureau of Economic Research.

Hall, Bronwyn, Adam B. Jaffe, and Manuel Trajtenberg, 2005, Market value and patent citations, *RAND Journal of Economics* 36, 16–38.

He, Zhongzhi, Jiaping Qiu, and Tingfeng Tang, 2014, Hedge fund activism and corporate innovation, Working paper, McMaster University.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru and Noah Stoffman, 2014, Technological innovation, resource allocation and growth, Working paper, Massachusetts Institute of Technology.

Holmstrom, Bengt, 1989, Agency costs and innovation, *Journal of Economic Behavior and Organization* 12, 305–327.

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *American Economic Review* 76, 323-29.

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

Krishnan C.N.V., Frank Partnoy, and Randall S. Thomas, 2015, Top Hedge Funds and Shareholder Activism, Working paper, Vanderbilt University.

Lai, Ronald, Alexander D'Amour, Amy Yu, Ye Sun, and Lee Fleming, 2013, Disambiguation and co-authorship networks of the U.S. patent inventor database (1975–2010), Harvard Business School.

Lerner, Josh, Morten Sorensen, and Per Stromberg, 2011, Private equity and long-run investment: The case of innovation, *Journal of Finance* 66, 445–477.

Pastor, Lubos and Pietro Veronesi, 2009, Technological revolutions and stock prices, *American Economic Review* 99, 1451–83.

Scharfstein, David, and Jeremy Stein, 2002, The dark side of internal capital markets: Divisional rent-seeking and inefficient investment, *Journal of Finance* 55, 2537–2564.

Serrano, Carlos, 2010, The dynamics of the transfer and renewal of patents, *RAND Journal of Economics* 41, 686–708.

Seru, Amit, 2013, Firm boundaries matter: Evidence from conglomerates and R&D activity, *Journal of Financial Economics* 111, 381–405.

Stein, Jeremy, 1988, Takeover threats and managerial myopia, *Journal of Political Economy* 96, 61–80.

Stein, Jeremy, 1989, Efficient capital markets, inefficient firms: A model of myopic corporate behavior, *Quarterly Journal of Economics* 104, 655–669.

Stein, Jeremy, 2003, Agency, information and corporate investment, *Handbook of the Economics of Finance* 1, 111–165.

Wang, Ying and Jing Zhao, 2015, Hedge funds and corporate innovation, *Financial Management*

Appendix A-1. Variable Definition and Description

Variable	Definition and Description
	a. Innovation Variables
New Patents	Number of patent applications filed by a firm in a given year.
Average Citations	Average number of 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 classified as 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 classified as 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 Appendix A-2. Please refer to Akcigit, Celik and Greenwood (2013) for a detailed discussion of this measure.
	b. Innovative Resource Reallocation
Inventor leavers	An inventor is defined as a leaver of firm *i* in year *t*, if she generates at least one patent in firm *i* between [*t-3,t-1*] and generate 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 defined as 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 patent sold by a firm. Identified from Google Patent Transactions Database compiled by USPTO.
Patent Buy	Number of patent bought by a firm. Identified from Google Patent Transactions Database compiled by USPTO.
	c. Firm Characteristics
Age	Number of years since IPO. The natural logarithm of this variable is used in the paper.
Total Assets	Total assets (AT).
MV	Market value of the firm, defined as common shares outstanding (CSHO) times the

	share price close.
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).
R&D Expense	Research and development expenses (XRD).
R&D Ratio	Research and development expenses (XRD) scaled by total assets (AT).

Appendix A-2. Distance between a Patent and a Firm's Technology Stock

Following Akcigit, Celik and Greenwood (2013), 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,

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

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. In this paper, we follow Akcigit, Celik and Greenwood (2013) and use $\iota = 0.33, 0.66$ for our analyses.

Figure 1. Innovation Quantity and Quality around Hedge Fund Activism

This figure presents the dynamics in innovation in the years around the targeting by hedge fund activists. The coefficients and confidence intervals are estimated from the following specification:

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

The dummy variable $d[t+k]$ is equal to one if the observation is k years before (after) hedge fund activism (pseudo-event year for control firms), and zero otherwise. We plot the β_k coefficients which are the estimates for the differences in innovation trends between hedge fund targets and matched control firms. We employ the sample of hedge fund targets and matched firms, retaining only those target firms who file for a patent at least once before the event (the innovative firms). The unit of observation is at the firm(i)-year(t) level. The left panel plots the estimates for quantity of innovation as measured by the logarithm of the number of patents filed by firm i in year t. The right panel plots the estimates for quality of innovation as measured by the logarithm of the average citations received by patents filed by the firm in year t. Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed effects.

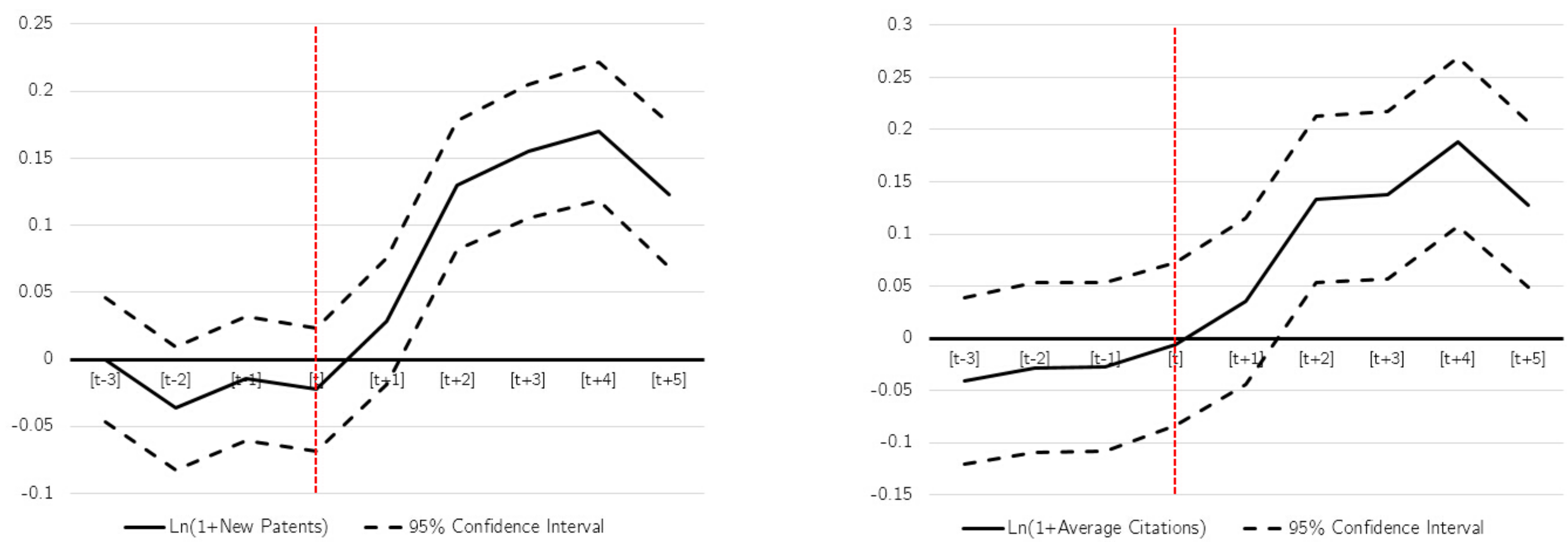
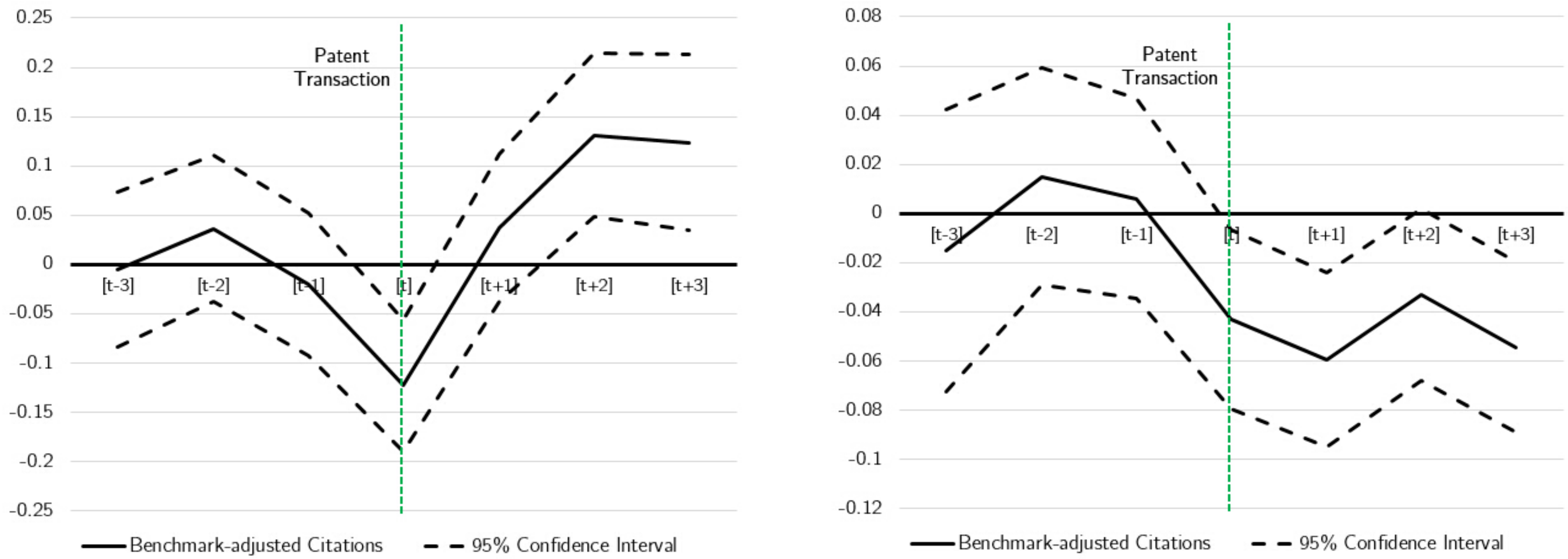


Figure 2. Citation Dynamics around Patent Transactions

This figure plots the coefficients β_k from the following regression at the patent (i)-year (t) level for each year from $k = -3, \ldots, +3$:

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

$Citation_{i,t}$ is the number of new citations a patent receives in a given year. The dummy variable *d[t – k]* (*d[t + k]*) is equal to one if the observation is *k* years before (after) the sale of patents, and zero otherwise. We run the regression separately for patents sold by target firms in the two years following hedge fund intervention (left panel) and for patents sold by matched non-target firms (right panel). We control for *Patent Age* measured as the logarithm of the patent age in year *t*. In addition, year and patent fixed effects α_t and α_i are included. The 95% confidence interval for each set of coefficients is indicated using dotted lines.



(a) Patent Transactions after HFA **(b) Patent Transactions of Control Firms**

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). Although we identify hedge fund activism events mainly through Schedule 13D filings, which are mandatory SEC filings in which hedge funds disclose stock 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 mid- and large-capitalization companies. Target firms are initially broadly defined as "innovative targets" if the firm filed at least one patent in any year prior to the activism event, and are later narrowly defined as "innovative targets" if the firm filed at least one patent between three years and one year prior to the activism event. Panel A reports the annual number of hedge fund activism events between 1994 and 2007, the representation of innovative target firms 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 representation 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*	
	(1)	(2)	(3)	(4)	(5)
Year	# of Events	% of Innovative Targets	# of Patents Owned by Targets (Median)	% of Innovative Targets	# 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

	Activism Events	% of Innovative Targets (Patent(s) Filed Anytime Prior to Year t)	% of Innovative Targets (Patent(s) Filed from Year *t-3* to Year *t-1*)
Consumer Nondurables	94	36.17%	21.28%
Consumer Durables	47	61.70%	59.57%
Manufacturing	166	59.04%	46.39%
Energy	64	9.38%	3.13%
Chemicals and Allied Products	33	60.61%	48.48%
High Tech	346	51.45%	41.04%
Tele and Communications	73	12.33%	9.59%
Utilities	29	6.90%	3.45%
Wholesale and Retail	225	9.33%	5.78%
Healthcare, Medical Equipment, and Drug	192	53.13%	46.35%
Finance	238	5.04%	2.10%
Others	263	15.97%	9.89%
Full Sample	1,770	31.24%	24.07%

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 at least one patent prior to the year of hedge fund 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 industry (2-digit SIC) with the closest propensity score, where the propensity score is estimated using size (logarithm of total assets) and market to book ratio both in one year and three years prior to intervention. For each variable, we report the mean, standard deviation, 25^{th}, 50^{th} and 75^{th} percentiles. We also report the *t*-statistics for the differences in means between the target and matched firms. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in the Appendix.

	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)
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 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)
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 Patent Portfolio Diversity	0.31	0.31	0.00	0.25	0.63	0.33	0.31	0.00	0.34	0.64	-0.02	(-1.15)
Firm Patenting Distance	0.67	0.30	0.53	0.76	0.90	0.68	0.27	0.54	0.74	0.88	-0.01	(-0.46)
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)

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:

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

We employ the sample of hedge fund targets and matched firms, retaining only those target firms who file for a patent at least once before the event (the innovative firms). The sample only consists observations from 5 years prior to and 5 years post intervention (of its matched target). *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. In column (1), the dependent variable is R&D expenditures scaled by firm assets while in column (2) the dependent variable is the 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-1. Column (7) studies the right-tail of innovation quality by performing the analysis on the average quality of the top 20% most cited patents produced by firm i in year t. Control variables include the natural logarithms of firm market capitalization and firm age. All specifications include firm and year fixed 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) Quality of Top 20% Patents
I(Target) × I(Post)	-0.151	-11.007***	0.151***	0.155***	0.027***	0.009	0.172**
	(-1.323)	(-3.086)	(3.711)	(3.071)	(2.816)	(1.109)	(2.250)
I(Post)	0.061	4.648	-0.060*	0.007	-0.049***	-0.003	-0.100
	(0.430)	(1.044)	(-1.935)	(0.176)	(-3.973)	(-0.279)	(-1.462)
ln(MV)	-0.580***	5.361***	0.047***	0.048***	0.012***	0.009***	0.096***
	(-13.736)	(4.058)	(4.076)	(3.310)	(3.476)	(2.963)	(3.683)
ln(Age)	0.014	-2.713	-0.029	-0.084	-0.022*	0.008	-0.281***
	(0.108)	(-0.677)	(-0.747)	(-1.506)	(-1.888)	(0.715)	(-3.805)
Constant	8.872***	8.273	-0.009	0.432	0.198*	0.021	0.741
	(7.347)	(0.219)	(-0.029)	(1.064)	(1.781)	(0.274)	(1.433)
Observations	8,016	8,016	8,016	8,016	3,218	2,763	8,016
R-squared	0.888	0.909	0.632	0.555	0.506	0.460	0.576
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Hedge Fund Activism, Innovation, and the Diversity of Innovation

This table documents the interaction between hedge fund activism and diversity in corporate innovation and the resulting impact on corporate innovation. The sample consists of the innovative target and matched firms, where innovative firms are defined as all firms that file for a patent at least once prior to the event. In Panel A, we use a difference-in-difference-in-difference specification:

$$\begin{aligned} y_{i,t} = \alpha_t + \alpha_i &+ I(HighDiv) \cdot [\beta_1 \cdot I(Post) \times I(Target) + \beta_2 \cdot I(Post)] \\ &+ I(\, LowDiv\,) \cdot [\beta_3 \cdot I(Post) \times I(Target) + \beta_4 \cdot I(Post)] \\ &+ \gamma \cdot Control_{i,t} + \varepsilon_{i,t}\,. \end{aligned}$$

I(Target) and *I(Post)* are as defined in Table 3. *I(HighDiv)* and *I(LowDiv)* are dummy variables indicating whether a firm is above or below median in terms of its patent portfolio diversity, measured at event 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, β_2) are reported in column (1), and those interacted with *I(LowDiv)* (β_3, β_4) are reported in column (2). The *F*-test statistic (with p-value in the parentheses) for the equality of the coefficients associated with *I(Post)×I(Treated)* is reported in column (3). In columns (4) to (6), we perform the same analysis as the previous three columns except that the dependent variable is replaced by the logarithm of citations per patent (plus one). Control variables include the logarithms of firm market capitalization and firm age.

In Panel B we focus on the outputs from innovation in the central technology classes of a firm, where a technology class is defined as central to a firm if at least 20% of the firm's patent stock is in that class. We use the following specification:

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

I(Target) and *I(Post)* are as defined in Table 3. The results are reported for measures calculated among key and non-key technology classes separately. In columns (1) and (2), the dependent variables are constructed by counting the number and average citations of new patents in the central technology classes of a firm. Column (3) and (4) studies the innovation strategies (intensity of exploration) of target firms subsequent to hedge fund activism. *Explorative* (*exploitative*) measures the intensity with which a firm innovates based on knowledge new (old) to the firm and the Appendix contains more detailed description of this variable. Column (5) to (8) are analogous to (1) to (4) except that the measures are constructed using innovation not belonging to the key technology classes of the firm. Control variables include the natural logarithm of firm market capitalization and firm age. All specifications include industry 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 the 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)	0.211***	0.068	4.12**	0.189***	0.078	1.81
	(4.458)	(1.232)	(4.34%)	(3.103)	(1.294)	(17.92%)
I(Post)	-0.057	-0.032		-0.031	0.032	
	(-1.468)	(-0.671)		(-0.717)	(0.589)	
ln(MV)	0.046***			0.047***		
	(4.760)			(3.631)		
ln(Age)	-0.032			-0.089*		
	(-0.948)			(-1.896)		
Observations	8,016			8,016		
R-squared	0.665			0.588		
Year FE	Yes			Yes		
Firm FE	Yes			Yes		

Panel B: Effect on Key and Non-Key Technology Classes

	Effect on Key Technology Classes				Effect on Non-key Technology Classes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(1+# New Patents)	ln(1+Ave.Citation)	Explorative	Exploitative	ln(1+# New Patents)	ln(1+Ave.Citation)	Explorative	Exploitative
I(Target) × I(Post)	0.162***	0.151***	0.033**	-0.039	0.051	-0.023	-0.030	0.004
	(2.858)	(3.190)	(2.107)	(-0.689)	(1.232)	(-0.488)	(-0.490)	(0.068)
I(Post)	0.008	0.045	-0.030**	0.023	-0.085***	0.046	0.016	0.025
	(0.203)	(1.217)	(-2.008)	(0.459)	(-3.042)	(1.227)	(0.309)	(0.513)
ln(MV)	0.044***	0.038***	0.010**	0.003	0.049***	0.038***	-0.000	-0.000
	(3.334)	(2.723)	(2.048)	(0.185)	(4.826)	(2.816)	(-0.014)	(-0.007)
ln(Age)	0.150***	0.078	-0.031	-0.078*	-0.063	0.079	-0.045	-0.070*
	(2.759)	(1.246)	(-1.646)	(-1.819)	(-1.376)	(1.264)	(-0.904)	(-1.664)
Constant	-0.420	-0.032	0.204	1.172***	-0.130	-0.038	0.956***	1.141***
	(-1.085)	(-0.081)	(1.313)	(6.535)	(-0.410)	(-0.094)	(3.691)	(6.911)
Observations	8,016	8,016	3,218	3,218	8,016	8,016	3,218	3,218
R-squared	0.649	0.522	0.270	0.499	0.574	0.526	0.543	0.498
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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:

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

The sample consists of the innovative target and matched firms, where innovative firms are defined as all firms that file for a patent at least once prior to the event. In Panel A, the dependent variables are the numbers of patents bought and 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)* and *I(Post)* are defined as in Table 3. Control variables include the logarithms of firm market capitalization and firm age. All specifications also include year and industry (or firm) fixed effects. 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. (2013). The two columns vary in the value (0.33 and 0.66) of the weighting parameter ι (See Akcigit et al. (2013) for a more detailed description of this variable and the 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. Panel C analyzes the dynamics of citations for those patents sold by target firms within two years post-activism (columns 1, 3, and 5), and, for comparison, those of patents sold by matched firms (columns 2, 4, and 6). The dependent variable is the number of new citations a patent receives in a given year. The dummy variable $d[t-k]$ ($d[t+k]$) is equal to one if the observation is *k* years before (after) the sale of a patent. We control for the logarithm of patent age. All specifications include year, patent or technology-class 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.

Panel A: Patent Transaction Intensity around Hedge Fund Activism

	(1)	(2)	(3)	(4)
	$\frac{Patent\ Sales}{Patentss\ Owned}$ $(in\ \%)$		$\frac{Patent\ Purchases}{Patentss\ Owned}$ $(in\ \%)$	
I(Target) × I(Post)	0.548*	0.578*	0.165	0.257**
	(1.723)	(1.849)	(1.407)	(2.223)
I(Target)	-0.271		0.120	
	(-1.112)		(1.092)	
I(Post)	0.300	-0.265	0.120	-0.098
	(1.045)	(-0.707)	(1.114)	(-0.796)
ln(MV)	0.007	-0.031	0.089***	0.025
	(0.157)	(-0.283)	(4.303)	(0.632)
ln(Age)	-0.311***	0.418	-0.261***	-0.288
	(-2.794)	(1.143)	(-3.781)	(-1.503)
Constant	1.339***	-0.516	4.738	4.966
	(3.419)	(-0.583)	(1.277)	(1.341)
Observations	7,930	7,930	7,930	7,930
R-squared	0.032	0.156	0.027	0.173
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 (ι = 0.33)		Distance Measure (ι = 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

Panel C: Efficiency Gains for Patents Sold by Targets of Hedge Fund Activists

	(1) Patent Sold After HFA	(2) Patent Sold by Non-target	(3) Patent Sold After HFA	(4) Patent Sold by Non-target	(5) Patent Sold After HFA	(6) Patent Sold by Non-target
d[t-3]	-0.061	-0.036	-0.035	-0.047	-0.005	-0.015
	(-1.573)	(-1.187)	(-0.900)	(-1.535)	(-0.124)	(-0.513)
d[t-2]	-0.022	-0.008	0.000	-0.004	0.036	0.015
	(-0.584)	(-0.344)	(0.011)	(-0.182)	(0.956)	(0.666)
d[t-1]	-0.085**	-0.001	-0.065*	0.002	-0.020	0.006
	(-2.377)	(-0.067)	(-1.823)	(0.076)	(-0.546)	(0.293)
d[t]	-0.202***	-0.009	-0.185***	-0.007	-0.123***	-0.043**
	(-6.462)	(-0.509)	(-5.933)	(-0.366)	(-3.630)	(-2.324)
d[t+1]	-0.041	-0.012	-0.030	-0.009	0.037	-0.060***
	(-1.128)	(-0.673)	(-0.819)	(-0.504)	(0.966)	(-3.299)
d[t+2]	0.034	0.034*	0.036	0.036**	0.131***	-0.033*
	(0.812)	(1.893)	(0.855)	(1.988)	(3.095)	(-1.847)
d[t+3]	0.112**	0.050***	0.109**	0.044**	0.124***	-0.054***
	(2.476)	(2.743)	(2.418)	(2.420)	(2.711)	(-3.074)
Ln(Patent age)	0.006***	0.010***	0.016***	0.020***	-0.049***	-0.052***
	(4.316)	(6.979)	(10.089)	(12.965)	(-6.518)	(-7.125)
Observations	1,225,191	1,291,915	1,225,191	1,291,915	1,225,191	1,291,915
R-squared	0.196	0.198	0.199	0.201	0.447	0.449
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Patent FE	No	No	No	No	Yes	Yes
Tech Class FE	No	No	Yes	Yes	No	No
F-Test						
[t]-[t-3]	7.68	0.56	8.81	1.24	6.67	0.72
p-val	0.01%	45.59%	0.00%	26.53%	0.01%	39.5%
[t+3]-[t]	31.51	5.17	27.85	3.81	23.31	0.24
p-val	0.00%	2.30%	0.00%	5.11%	0.00%	62.47%
DiD([t]-[t-3])	1.19		4.84		0.00	
p-val	27.54%		2.79%		96.92%	
DiD([t+3]-[t])	24.87		18.64		6.12	
p-val	0.00%		0.00%		1.34%	

Table 6. Inventor Mobility around Hedge Fund Activism Events

This table analyzes inventor mobility around hedge fund interventions (Panel A) and the effects of hedge fund activism on inventor productivity subsequent to inventor turnover (Panel B). The sample consists of hedge fund targets and matched firms which file for a patent at least once before the event (i.e., the firms broadly defined as innovative). A "leaver" is an inventor who leaves her firm during a given year, who generates at least one patent in the firm before the year of intervention, and who generates one patent in a different firm after the year of intervention. A "new hire" is an inventor who has been newly hired by a given firm in a given year, who generates at least one patent in a different firm before the year of intervention, and who generates at least one patent in the firm after the year of intervention. A "stayer" is an inventor who stays with her firm during a given year and who generates at least one patent both before and after the year of intervention. An inventor is considered to generate a patent if she files for patent during the relevant time period and that request is ultimately granted. *I(Target)* and *I(Post)* are as defined in Table 3. Control variables include the natural logarithms of firm market capitalization and firm age, and total R&D scaled by total assets. Panel A adopts the following difference-in-differences specification:

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

The dependent variables in columns (1) and (2) are the natural logarithms of the number of leaving inventors (plus one) and the number of newly hired inventors (plus one), respectively. All the specifications include industry and year fixed effects. Panel B adopts a similar specification as in Panel A at the inventor-year level. The dependent variable is the change in an inventor's productivity around the event year, defined as the difference between the number of patents (or the number of citations) belonging to the inventor in the [t+1, t+3] and [t-3, t-1] periods, where *t* is the year of intervention. 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 Events

	(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)
Constant	-0.507***	-0.146	-0.245	0.134
	(-2.914)	(-0.743)	(-1.327)	(0.695)
Observations	8,016	8,016	8,016	8,016
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: Inventor Productivity Subsequent to Hedge Fund Activism Events

	(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	0.068	0.099	0.067	0.043	0.043	0.036
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Divestitures around Hedge Fund Activism Events

This table analyzes asset divestitures around hedge fund activism. Panel A displays annual summary statistics of divestitures, defined as the divestment of more than 10% of a firm's total assets during [t, t+2] where *t* is the year of intervention. *Mean # of divestitures* is the average number of divestitures per activism event, and *% with ≥1 Divestiture* is the proportion of activism events that result in at least one divestiture. Panel B examines the relation between divestitures and reallocation of innovative resources (inventors and patents). The sample is the cross-section of all activism events involving innovative target firms. The dependent variable in column (1) is the logarithm of the number of patents sold during the same time period (plus one). The dependent variable in column (2) is the logarithm of the number of inventors leaving the firm within three years after the hedge fund intervention (plus one). The key independent variable is *Divestiture*, a dummy equal one if a divestiture event occurs within three years after the hedge fund intervention. Control variables include the logarithms of firm market capitalization and firm age. All specifications include industry 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: Summary of Divestitures around Hedge Fund Activism Events

		All Firms		Innovative Firms	
Year	# of Activism	Mean # of Divestitures	% with >=1 Divestiture	Mean # of Divestitures	% with >=1 Divestiture
1994	8	3.75	57.14%	5.50	75.00%
1995	26	0.58	34.62%	0.67	41.67%
1996	72	0.46	29.69%	0.65	29.41%
1997	137	0.32	19.30%	0.48	17.02%
1998	114	0.34	27.78%	0.33	23.81%
1999	80	0.35	31.15%	0.55	40.00%
2000	79	0.27	26.23%	0.52	42.86%
2001	74	0.42	38.33%	0.50	33.33%
2002	100	0.34	25.29%	0.31	28.95%
2003	86	0.51	33.33%	0.84	43.24%
2004	108	0.45	31.25%	0.75	38.10%
2005	157	0.38	27.34%	0.51	35.09%
2006	185	0.38	28.07%	0.51	33.33%
2007	206	0.42	27.53%	0.53	30.68%
Pooled Average		0.41	28.41%	0.57	32.53%

Panel B: Divestitures and Innovative Resource Reallocation

	(1) Ln(1+# of Patents Sold)	(2) Ln(1+# of Leavers)
Divestiture	0.365***	0.106*
	(2.899)	(1.828)
ln(MV)	0.087***	0.067***
	(2.644)	(4.025)
ln(Age)	-0.016	-0.043
	(-0.248)	(-1.367)
Constant	-0.276	0.519**
	(-1.097)	(2.045)
Observations	541	541
R-squared	0.349	0.375
Year FE	Yes	Yes
Industry FE	Yes	Yes