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Shareholder Power and Corporate Innovation: Evidence from Hedge Fund Activism

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Abstract

We examine whether hedge fund activism affects corporate innovation. We find that firms targeted by hedge fund activists experience an improvement in innovation efficiency within three years after the intervention as evidenced by a significant drop in R&D spending but an increase in innovation output measured by both patent counts and citations. We then show that hedge fund activists improve target firms' innovation efficiency via the reallocation of innovative resources and the redeployment of human capital. Finally, we show that the link between hedge fund interventions and improvements in innovation efficiency is potentially driven by firms' assets reallocation triggered by activists. Our paper is the first study that sheds light on the real effect of strengthened shareholder power in reshaping corporate innovation.

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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 pressure from the stock market on managerial incentives to engage in value-relevant innovative activities which are not easily assessed by the market. Most importantly, "managerial myopia," due to stock market performance pressure, has been a recurring concern (Stein, 1988, 1989). In recent years, the debate has reached a heightened level as activist hedge funds have come to epitomize the movement for stronger shareholder rights and empowerment.

Between 1994 and 2007, there have been more than 2,000 events of hedge fund activism where hedge funds have acquired significant but strictly minority equity stakes (typically 5-10%) in companies that they perceived as undervalued, and then proposed changes in payout policies, business strategies, and corporate governance, often publicly and aggressively.[1] Recent studies, covering both the U.S. and international markets, have documented a robust positive stock price reaction around the announcement date in the range of 5-10%. Moreover, the interventions are not followed by declines stock returns or operating performance during the five-year window after the initial short-term gain.[2] Yet, the long-term impact of hedge fund activism is more difficult 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' agenda is biased towards the pursuit of short-term stock gains at the expense of firms' long-term value.[3]

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 at the same time is also most susceptible to potential short-termism. While hedge fund activism might have a direct impact on corporate innovation as hedge funds increasingly target technology companies,[4] the indirect effect is likely to be more wide spread as a byproduct of changes in corporate financial and business strategies. For example, companies targeted by activism hedge funds tend to increase payout (and hence leave less liquidity for discretionary spending) and reduce overall investment. Since R&D activities require

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

[2] See Brav, Jiang, Partnoy, and Thomas (2008), Klein and Zur (2009), Clifford (2008), Greenwood and Schor (2009) for U.S. companies; and Becht, Franks, Mayer, and Rossi (2009), Becht, Franks, and Grant (2010) for non-U.S. markets.

[3] See Bebchuk, Brav, and Jiang (2013) for a detailed discussion regarding the debate.

[4] Activist hedge fund engagements with technology powerhouses Microsoft, Google, and Apple in recent years all involve the target firms' R&D policies. 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/

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.

Neither the direction nor the magnitude of activists' impact on overall innovation activities is *a priori* clear. First, a negative impact might arise 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. The lack of observability and predictability alters incentives such that management, responding to pressure from current shareholders, might adopt investment/innovation policies that are detrimental to long-term firm value. More powerful current shareholders could lead to greater misalignment. 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 form expectations about the value of innovations. Recent work by Cohen, Diether, and Malloy (2013) offers some support to this argument. They show that the stock market fails to incorporate information of past successes when valuing innovation. However, it is not clear whether investors systematically undervalue innovation as opposite predictions may also arise from equilibrium models (Pastor and Veronesi (2009)).

Second, though management has preferences and objectives that are different from those aimed at firm value maximization, the order of the relative preference is not *a priori* clear, either. Like any other investment decisions, 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, overinvestment may arise if specialized investment entrenches the management (Scharfstein and Stein (2002)) or if managers derive private benefits from such activities. In such a scenario, shareholders can legitimately demand that firms spend fewer resources on innovative activities. An opposite ordering is also plausible: shareholders may demand higher levels of R&D than the management think is appropriate if diversified investors have more capacity to absorb innovation risk (Aghion, Van Reenen, and Zingales (2013)).

To inform this debate this paper provides the first direct evidence on the effect of shareholder power, in the form of hedge fund activism, on firm innovation. To set the stage, we first examine the dynamics of innovation's inputs and outputs surrounding the year of the hedge fund intervention. Consistent with previous findings that targeted firms reduce investment, we find that their R&D spending also drops significantly for several years after the intervention. Interestingly, innovation output measured by patent counts, citation counts per patent, patent generality, and patent originality do not appear to shrink and some of these measures even outperform those of their industry peers. Relatedly, a firm's innovation output is positively associated only with the ownership by activist hedge funds, but not with the ownership by non-activist hedge funds. The preliminary evidence suggests that firms tend to improve innovation efficiency in the period following the targeting by hedge funds.

Next, we explore two mechanisms through which hedge fund activism impacts targeted firms' innovation efficiency. First, hedge fund activism might be associated with a more efficient reallocation of innovative outputs. Specifically, patents sold within three years post hedge fund targeting exhibit significantly higher citations (a common proxy for patent productivity) relative to their own history or to their peers (patents in the same technology class with similar vintage) during the first two years post transaction, a pattern that was nonexistent before intervention. Patents sold by non-targeted firms do not experience such an improvement. This contrast suggests that firms targeted by hedge funds are more likely to engage in transactions with new owners who can operate those patents more productively, contributing to the efficiency gain we observe in the previous test.

Second, redeployment of innovators also explains the improvement in innovation efficiency. We follow the productivity (in terms of both patents filed and citations per patent) separately for inventors who stay with or leave the targeted companies, as well as those that are hired anew, post hedge fund intervention. A set of consistent patterns emerge: The inventors that target firms retain are more productive than "stayers" in non-target firms; the inventors who leave following hedge fund intervention become more productive with their new employers; and finally, the inventors newly hired post intervention also outperform their own past. The combined evidence is consistent with a positive outcome due to the reshuffling of human capital where the key innovative personnel are matched or re-matched to environments where they can be more productive.

The evidence that we document linking hedge fund activism with more efficient reallocation of innovation outputs (patents) and resources (human capital) is intriguing in light of the fact that in most interventions hedge funds do not directly target companies' R&D or general innovative activities.[5] Similarly, activists rarely possess the precise in-depth scientific knowledge that is required to guide the innovative process. We therefore also 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 (2013)) showing that hedge funds facilitate asset reallocation in the form of sale of assets, segments, or even 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. This effect is also observed in the

[5] There are exceptions. For example, the activist hedge fund Starboard Value LP is known for targeting intellectual property-rich firms with explicit demands about the firms' R&D and patenting policies.

subsample of events where divestitures took place despite managerial resistance—where there is no doubt that the asset reallocation should be attributed to the intervention.

Our study presents a more nuanced picture than a straight answer to whether hedge fund activism encourages or impedes corporate innovation. While inputs to innovation, measured by R&D expenditures, decline post hedge fund intervention, the output level as well as quality as measured by patenting activities hold up well or even improve. This suggests that firms become "leaner" but not "weaker" on the innovative front. Moreover, the efficiency gains emanate mostly from the extensive rather than the intensive margin, that is, through the redeployment of innovative assets—be it patents or innovators. Such a pattern echoes, and may well be a byproduct of, hedge funds' role in improving physical assets productivity through reallocation (i.e., sale of plants and refocusing of the business) as documented by Brav, Jiang, and Kim (2013). Moreover, these results also offer an explanation as to why the positive stock market reaction to announced hedge fund activism is highest when activists propose major assets restructuring, including a sale of assets, 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 determinants include: Firm's going public decision (Bernstein (2012)), anti-takeover provisions (Chemmanur and Tian (2013)), institutional ownership (Aghion, Van Reenen, and Zingales (2013)), stock market liquidity (Fang, Tian, and Tice (2013)), and labor union (Bradley, Kim, and Tian (2013)). Our study connects innovation to an increasingly important form of market-based corporate governance, which is shareholder empowerment represented by hedge fund activism. Closest to ours are recent papers on the effect of private equity/venture capital involvement with innovation (Lerner, Sorensen, and Stromberg (2011), Chemmanur, Loutskina, and Tian (2013)).

Activist hedge funds are, however, critically different from PE/VC in that their primary role is not financing but acting as vigilant external monitors without taking control of the firm. Relatedly, activist hedge funds do not target fledging enterprises which need nurturing; instead they seek more mature firms that are prone to agency problems of free cash flows as in Jensen (1986). The different results between our study and those on PE/VC mostly reflect the target firms' different stages in their life cycle.

The paper proceeds as follows. Section 2 presents the various datasets that we use to form our measures of inputs and outputs to the innovation process as well as the hedge fund activism sample used in the analysis. Section 3 documents the dynamics of inputs to innovation in the form of R&D expenditures and then outputs in the form of patents and patents citations in the years before and after activists' intervention. In Section 4 we focus on the reallocation of innovative resources. We document how hedge fund activists push target firms to efficiently reallocate their innovative resources by selling their existing patents. We also examine the impact of the intervention on the redeployment of human capital by tracking the quantity and quality of the patents generated three groups of inventors: those that stay employed at the target firm, those that leave the target firm, and inventors that were hired by the target firm post-intervention. Section 6 runs a set of identification tests. We conclude in Section 7.

2. Data and Key Variables

2.1 Data Sources and Sample Construction

2.1.1 Hedge fund activism data

The database of hedge fund activism events, covering the period of 1994-2007, is an extended sample of that used in Brav, Jiang, and Kim (2009) based on the same sample selection criteria. These events are identified mainly through Schedule 13D filings to the SEC, in which hedge funds disclose stock ownership exceeding 5% with an intention to influence corporate policy or control. We also conduct news searches to identify activist events targeted at mid- to large-cap companies (above $1 billion) with ownership stakes between 2% and 5%. We collect detailed information on key aspects of each event from the initial and amended 13D filings via the SEC's EDGAR system and by news searches.

2.1.2 Innovation data

We follow existing literature and measure firm innovation using two proxies. Our first proxy is R&D expenditures from Compustat. Apart from the incompleteness of this data it is well known that R&D expenditures capture only one particular observable quantitative input and are also sensitive to accounting norms such as whether it should be capitalized or expensed (Acharya and Subramanian (2009)).[6]

Our second measure of firm innovation is its patenting activity, which we believe better captures a firm's innovation intensity since patenting is an output variable. It thus encompasses the successful use of innovation inputs, both observable and unobservable. We obtain information on firms' patenting activity from the latest version of the NBER patent database which provides annual information from 1991 to 2006 on patent assignee names, the number of patents, the number of citations received by each patent, the technology class of the patent, a patent's application year, and a patent's grant year. Our use of patenting to capture firms' innovation output has become standard in the innovation literature (e.g., Acharya and Subramanian (2009); Aghion, Van Reenen, and Zingales, (2013); Chemmanur and Tian (2013)).

[6] Information on R&D expenditures, reported in Compustat, is quite unreliable which may introduce a significant measurement error problem. Moreover, more than 50% of firms do not report R&D expenditures in their financial statements. Since the lack of reported R&D expenditures does not necessarily mean that a firm did not undertake innovative activities, replacing missing values of R&D expenditures with zeros, a common practice in the existing literature, introduces additional noise that could bias the estimated effect on innovation measured by R&D expenditures.

In addition to general patenting activities, two additional sources of information are critical to our analysis on the reallocation of human capital. First, we obtain individual inventor information from the Harvard Business School (HBS) patent and inventor database in order to track inventor mobility associated with hedge fund activism.[7] The HBS patent and inventor database, covering the period of 1991 -2010, provides information for inventors, the individuals who receive credit for producing the patent, and assignees, the entity that owns the patents, which can be a government, a firm, or an individual. The database provides a unique identifier for each inventor so that we are able to track the mobility of individual inventors.[8]

Second, in order to analyze patent mobility associated with hedge fund activism, we gather details on patents transactions from 1991 to 2006 in text files for bulk downloading from Google Patent through a special arrangement with the USPTO.[9] This database provides detailed information about the name of the patent buyer (assignees), the name of the patent seller (assignors), the unique identifier of patents (patents numbers), and patents transaction date (the date at which the re-assignment was recorded at the patent office). We match the names of assignors and assignees from Google Patent with the NBER database using a standard spelling distance algorithm. This algorithm uses a score based on the inverse word frequency to match assignee names to possible company names (see Kogan, et al. (2013)).[10] After the initial name-matching run, we filter the matched results to minimize incorrect matching while at the same time extracting as many correct matches as possible. In addition, we manually match unmatched assignors and assignees whenever possible. Finally, we follow Serrano (2010) to conservatively drop the assignments that appear not to be associated with an actual patent transaction. For example, some

[7] Available at http://dvn.iq.harvard.edu/dvn/dv/patent.
[8] See Lai, D'amour, Yu, Sun, and Fleming (2013) for details about the HBS patent and inventor database.
[9] Available at http://www.google.com/googlebooks/uspto-patents.html.
[10] The algorithm is based on code provided by Jim Bessen, which is available at the following website: https://sites.google.com/site/patentdataproject/Home/posts/Name-matching-tool

assignments are recorded as administrative events such as a name change, a correction, a security interest, etc. We also exclude the transaction of patents within firm boundaries such as assignments representing transactions between employees (inventors) and their employers (assignees).

2.2 Key Variables

2.2.1 Number of Patents and Citations

Based on the information retrieved from the NBER patent databases, we construct two patenting measures for a firm's innovation output. The first measure is a firm's number of patent applications filed in a year that are eventually granted. We use a patent's year of application instead of its grant year since the year of application is likely to better capture the actual time of innovation (Griliches, Pakes, and Hall, (1988)). Although straightforward to compute this measure cannot distinguish groundbreaking innovations from incremental technological discoveries. To further assess a patent's influence we construct a second measure of corporate innovation productivity by counting the number of citations each patent receives in subsequent years. Controlling for firm size, the number of patents captures innovation quantity while citations-per-patent captures the quality of innovation output. To reflect the long-term nature of investment in innovation, both measures of innovation output are measured one, two, and three years into the future in the panel data regression framework.

To address the truncation problems associated with the NBER patent databases we adjust the two main measures of innovation (the patent counts and patent citations) following the existing innovation literature. The first truncation problem arises as patents appear in the database only after they are granted. In fact, we observe a gradual decrease in the number of patent applications that are eventually granted as we approach the last few years in the sample period. This is because of the significant lag between a patent's year of application and the year in which it is eventually granted (about two years on average). Many patent applications filed during the latter years in the sample were still under review and have not been granted by 2010. Following Hall, Jaffe, and Trajtenberg (2001, 2005), we correct for this truncation bias by using “weight factors” that capture the shape of the application-grant empirical distribution.

The second type of truncation problem impacts our measure of citation counts, as a patent can keep receiving citations over a long period of time although we only observe citations received up to 2010. Following the same reference we correct for this truncation bias by dividing the observed citation counts by the fraction of predicted lifetime citations that is actually observed during the lag interval (the shape of the citation-lag distribution). The resulting distribution of patent grants in the pooled firm-year sample is right skewed, with more than half of firm-year observations having zero patents or citations. Due to the right-skewed distributions of patent counts and citations per patent we use the natural logarithm of one plus the weight-factor adjusted patent counts and the natural logarithm of one plus the citation-lag adjusted citations per patent as the main innovation measures in our analysis.

Note that the NBER Patent and Citation database is not affected by firm survivorship by its structure. As long as a patent application is eventually granted, it is attributed to the applying firm at the time of application even if the firm later gets acquired or goes bankrupt. Moreover, since patent citations are attributed to a patent rather than the applying firm, the patent granted to a firm that later gets acquired or goes bankrupt can still keep receiving citations long after the firm disappears.

It is important to note that using patenting activity to measure innovation is not without limitations. For example, different industries have various innovation propensity and duration. The innovation process by nature is longer and riskier in the pharmaceutical industry than in the software development industry. One might therefore observe fewer patents generated in the pharmaceutical industry in a given time period but this does not necessary imply that pharmaceutical firms are less innovative than software firms. However, we believe that an adequate control for heterogeneity in industries and firms should alleviate this concern and lead to reasonable inferences that can be applicable across industries and firms.

2.2.2 Patent Originality and Generality

While a higher citation count is typically interpreted as a patent having greater impact, the distribution of citations a patent is making and receiving is also important. Following Hall, Jaffe, and Trajtenberg (2001) we consider two alternative patent-based measures: patent originality and generality. 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. Both patent originality and generality reflect the fundamental importance of the innovation being patented. 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. The higher a patent's originality score the more that the patent draws upon a more diverse array of existing knowledge. 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. The higher a patent's generality score, the more that the patent is being drawn upon by a more diverse array of subsequent inventions.

2.3 Descriptive statistics

We merge the list of hedge fund activism events with the databases descried in Section 1.1, including the NBER Patent Citation database, the HBS inventor database, the Google patent transaction database, the CRSP/Compustat merged database, and the SDC M&A database. The final sample includes 1,640 hedge fund activism events.

Table 1 reports summary statistics comparing the characteristics of target firms with those of all public firms on the CRSP/Compustat merged database. We include the following measures: the ratio of R&D to assets (*R&D/Assets*); total patents filed by a firm in a given year (*Patents*); total citations of the existing patents belonging to a firm (*All_cites*); citations per patent (*Cites_per_patent*), Generality and originality of patents (*Generality* and *Originality*). We also report key firm characteristics including market capitalization (*MV*), return on assets (*ROA*), assets tangibility, proxied by PP&E to total assets (*PPE/Assets*), the ratio of debt to total capital (*Leverage*), the ratio of capital expenditures to assets (*Capex/Assets*), and the ratio of market to book value of assets (q). Panel A, columns 1-3, report the median, mean, and standard deviation of the innovation measures and firm characteristics of hedge fund targeted companies in the year before they are targeted. An average target firm invests 4.8% of its assets in R&D, files 1.7 patents, and each patent receives a total of 1.5 citations in all future years.

We report in columns 4-6 the comparison with the universe of public firms (CRSP/Compustat merged database). Specifically, we select matched firms for each target firm from the same year, same industry, based on three-digit SIC, and same 5 by 5 size and book-to-market sorted portfolios. If the narrow criteria yield no match, we relax the industry grouping to two-digit SIC. When we describe target firms by size (market capitalization), the size matching criterion is dropped. When we describe target firms by Tobin's q, the book-to-market matching criterion is dropped. Besides the patent originality scores we do not observe a significant difference in other innovation variables between targets and their matched peers. Other firm characteristics are similar to those reported in Brav, Jiang, Partnoy, and Thomas (2008).

We report in panel B of Table 1 the proportion of the target firms that fall into each of the size quintile groups formed by the CRSP/Compustat firms. For innovation variables, because a significant proportion of firms have zero innovation inputs (R&D expenditures) or zero innovation outputs (patents and citations), we single out the proportion of firms when the innovation variable equals zero. This sorting is unconditional and is meant to offer an overview of where the target firms populate in the universe of US public firms. The target firms are on average more innovative than the rest of public firms because the proportion of firms with zero R&D expenditures, patents, and citations is smaller. The distribution of other target firm characteristics is comparable to that reported in Brav, Jiang, Partnoy, and Thomas (2008).

[Insert Table 1 here.]

3. Dynamics of Inputs/Outputs to Innovation around Hedge Fund Activism

As a first step, we explore the relation between activist hedge fund targeting and innovation inputs, proxied by firm R&D expenditures, and then outputs from the innovation using patents or patent citations. Specifically, we estimate various specifications of the following model:

$$Innovation_{i,t} = \alpha + \sum_{k=-3}^{3} \beta_k d_{i,t}[t+k] + \gamma' Controls_{i,t} + Year_t + Industry_j + Firm_i + \varepsilon_{i,t} \qquad (1)$$

where *i* indexes firm, *j* indexes industry, and *t* indexes time. The dependent variable is either the measure of innovation input or innovation output. The key independent variable in equation (1) is a set of firm-year dummy variables, *d[t-3],…, d[t+3],* that correspond to firm-year observations from three years before to three years after a firm is targeted by a hedge fund activist. This specification analyzes the dynamics of innovation input and output of the target firms before and after hedge fund targeting. Control variables include firm market capitalization and age. We cluster standard errors at the firm level.

Table 2 provides the regression results for R&D expenditures, our measure of input to innovation. The dependent variable in columns 1 and 2 is the dollar amount of R&D and in columns 3 and 4 it is R&D

scaled by the firm assets measured at the previous year-end. While yearly dummies are included in all of the specifications, we control for industry fixed effects in columns 1 and 3 and firm fixed effects in columns 2 and 4.

[Insert Table 2 here]

The post-event yearly coefficient estimates in columns 1 and 2 are generally negative and statistically significant in year t+3. The F-statistics testing the difference between the coefficients on year t and year t+3 are 9.83 and 13.60, respectively, and both are significant at the 1% level, suggesting that there is a significant drop in R&D expenditures in the three years post targeting. In columns 3 and 4 in which R&D scaled by assets is used as the dependent variable, however, we do not find this pattern and the F-statistics are small and insignificant. The difference is due to the fact that hedge fund activism is associated with reduced assets due to a drop in capital expenditures and an increase in the rate of asset sales (Brav, Jiang, and Kim (2013)). In other words, we find that R&D shrinks at a similar rate with firm assets post targeting.

Next, in Table 3, we explore the dynamics of outputs from innovation around hedge fund activism in the framework of equation (1). Specifically, in columns 1-2 and 5-6 we report the dynamics of our two main innovation outcome variables, patent counts and the number of future citations per patent. Then, in columns 3-4 and 7-8, we consider two additional innovation output variables, patent originality and generality, that measures the quality of innovation. These two measures, defined in Section 2.2.2, are based on the distribution of citations and capture the nature of the innovation being patented. Patents that cite a wider array of technology classes of patents are viewed as having greater originality while patents cited by a wider array of technology classes of patents are viewed as having greater generality.

[Insert Table 3 here]

We control for yearly dummies and industry fixed effects in columns 1-4 of Table 3. Hence, the results now mainly rest on cross-sectional variation in our innovation variables. While the coefficient estimates on the pre-targeting yearly dummies are positive and generally insignificant, those on post-targeting dummies are positive and significant, suggesting that patent quantity and quality improve post hedge fund targeting relative to their industry peers. In columns 5-8, we explore within-firm time-series variation by including firm fixed effects. This specification removes the statistical significance of all event dummy estimates suggesting that there is essentially no change in innovation output within the firm's own time series surrounding the hedge fund targeting. The evidence reported in Table 3 and in Table 2 suggests that while target firms inputs to innovation, namely, R&D expenditures, after hedge fund targeting, the output of these innovative activities does not appear to shrink and even exhibits a higher level compared to their industry peers, that is, the innovation efficiency of hedge fund target firms tends to improve post targeting.

It is worthwhile at this point to ask whether the link that we document between innovation output and activist hedge funds reflects a broader pattern in which the presence of other, non-activist hedge funds, is associated with improvement in innovation at portfolio firms.[11] In unreported results we estimate various forms of the following model:

$$Innovation_{i,t+n} = \alpha + \beta \cdot HF_{i,t} + \gamma' Controls_{i,t} + Year_t + Firm_i + \varepsilon_{i,t} \tag{2}$$

where *i* indexes firm, *t* indexes time, and *n* equals 1, 2, or 3. The dependent variables that we examine are the innovation output variables: patent counts, citations, patent generality, or patent originality. The key

[11] Wang and Zhao (2012) conclude that hedge fund ownership per se is positively associated with innovation output. We comparability we adopt their regression setup. In untabulated analysis we are able to replicate their findings using their sample period, 1998-2006, and their specifications using innovation level variables. We are, however, unable to replicate their results using the change in innovation variables.

independent variable is *HF,* a dummy variable that equals one if the average hedge fund ownership in a year is greater than 5%, or zero otherwise. For the construction of this variable, we use the same comprehensive list of hedge fund companies that file Form 13F during our sample period as in Agarwal, Fos, and Jiang (2013), and retrieve their quarter-end holdings from the Thomson Reuters ownership database. We include the following set of control variables: firm size, R&D expenditures, capital expenditures, asset tangibility, ROA, leverage, cash holdings, Tobin's Q, Herfindahl index, and firm age, and cluster standard errors at the firm level. Since our paper focuses on the effect of activist hedge funds, we attempt to distinguish between hedge fund ownership by activist hedge funds versus that by passive hedge funds.

When we set the hedge fund dummy to indicate greater than 5% ownership by the activist hedge funds in our sample, the coefficient estimates on this dummy are positive in all specifications and statistically significant in columns where innovation outputs are generated two and three years ahead. The economic effect of activist hedge fund ownership on innovation output is sizeable. For example, firms with more than 5% ownership by activist hedge funds generate 4.7% more patents compared to their counterparts within three years. However, when we examine the effect of ownership by non-activist hedge funds (the complement set of the subsample of activist funds) the coefficients estimates on the high ownership dummy across all specifications are insignificant, suggesting that it is hedge fund activism, rather than mere hedge fund ownership that affects a firm's innovation output.

4. Reallocation of Innovative Resources

We next explore how efficient reallocation of innovative resources contributes to the improvement of innovation output relative to inputs. We consider two channels. The first channel, examined in Section 4.1, considers the role that hedge fund activists' play in reallocating target firms' innovative resources by selling existing patents that are not best utilized by the current owners. We then proceed in Section 4.2 to consider a second channel via which activist hedge funds lead to the reallocation of human capital. Specifically, we track three groups of inventors, those that stay employed at the target firm, those that leave the target firm, and inventors that were hired by the target firm post-intervention. We measure both the quantity and quality of the patents generated by these three groups of inventors and document the change in these measures of innovation following activists' intervention.

4.1 Reallocation of Target Firm Patents

4.1.1 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. In the Schedule 13D, Starboard included a letter that the fund had sent to the CEO and Chairman, Tim Armstrong, two months beforehand on December 21, 2011. At that time the fund was still below the 5% threshold that triggers the filing of Schedule 13D. The letter includes a review of each of the firm's business units (Access, Search, Advertising Network, and Display), based on publicly available information, arguing that the management and the board need to consider various ways to enhance AOL's shareholder value.

> "Based on our detailed research and analysis conducted to date, we firmly believe that AOL is deeply undervalued. At the current price, we believe that AOL's market value reflects only the value of the Company's highly profitable Access business and its net cash position. This implies that investors are ascribing no value to AOL's media assets, including its Advertising Network, Search business, and extensive portfolio of Display properties. We believe that this valuation discrepancy is primarily 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 the hedge fund stating that the current state of affairs is unsustainable asking to establish direct engagement with the board in order to discuss ways to find strategic alternatives that would stabilize the company and improve on its operating performance and valuation. At this stage the fund did not mention the sale of AOL's portfolio of patents.

On February 27, 2012 Starboard filed an amendment to its 13D filing reporting that its stake size had increased to 5.2% The fund included a second letter that was sent to the board three days earlier in which it turned its focus on AOL's portfolio of intellectual property.

> "…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.

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

Soon thereafter, AOL indeed proceeded to retain Evercore Partners as financial advisers 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.[12]

The fund was, of course, supportive of this decision but nevertheless argued in another letter to the company that additional steps were needed to further improve the operating performance of the company and that it would proceed with the filing of proxy material for the nomination of their directors to the board at the upcoming annual meeting. The proxy fight was eventually resolved in mid-June 2012 with the company receiving the majority of the shares voted with all of its eight directors re-elected while the fund was not able get any of its three directors on the board. AOL share prices were up roughly 40% over the three months since the sale of the patents.

4.1.2 Reallocation of target firm patents

In this section we formally test whether sales of existing patent by target firms post intervention lead to efficiently reallocate their innovative resources. As discussed in Section 2.1.2, we compile a patent transaction dataset by first obtaining details of patents transactions from 1991 to 2006 from Google Patent through a special arrangement with the USPTO. This database provides very detailed information about the number of the patent buyer (assignees), the name of the patent seller (assignors), the unique identifier of patents (patents numbers), and patents transaction date (the date at which the re-assignment was recorded at the patent office). The secondary source of data we use is the NBER patent citation database. This database provides all the patents number and a bridge file that is linked to Compustat.

We use the number of new citations a patent receives in a year as a proxy for the market value of the patent. We therefore merge the information obtained from the NBER patent database about year-by-year

[12] 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.

total number of new citations an existing patent receives with our patent transaction file. Because the NBER database provides patent citation information only up to 2006, we restrict our sample for this analysis to 2006. The sample includes all the patents kept and sold by both target and non-target firms. The unit of observation in this analysis is patent-year. We estimate the following model:

$$Cite_{i,t} = \alpha + \sum_{k=-3}^{3} \beta_k d_{i,t}[t+k] * Tgt + \sum_{k=-3}^{3} \beta_k d_{i,t}[t+k] + \gamma PatentAge_{i,t} + Year_t + Patent_i + \varepsilon_{i,t}, \quad (3)$$

where i indexes patent and t indexes time. The dependent variable is the number of new citations an existing patent receives in a year. The key independent variable in equation (3) is a set of interactions between the target dummy and patent event-year dummy variables, *d[t-3],…, d[t+3],* that correspond to patent-year observations from three years before to three years after a patent is sold. We include patent age in the regressions to control for the citation cycle of a patent. We also include year and patent (or technology class) dummies to absorb time- and patent-specific unobservable characteristics. We cluster standard errors at the patent level.

We report the results modeling the new citations a patent receives (equation (3)) in Table 4. We use the OLS model in columns 1 and 2 and the Negative Binomial model in columns 3 and 4 since the dependent variable is a non-negative count variable. In columns 1 and 3, we consider all the patents sold after the hedge fund intervention year. We only include the patents sold within the first five years of the hedge fund intervention year in columns 2 and 4. The specification in equation (3) is essentially a difference-in-difference-in-differences model, where we are comparing new citations received by patents that are kept versus patents that are sold, patents of target versus patents of non-target, and an event period year (from three years before to three years after the patent transaction year) versus non-event period years.

[Insert Table 4 here]

In columns 1 and 2, the coefficient estimates on *Target*Yeara1* and *Target*Yeara2* are positive and significant, suggesting that relative to patents that have not been sold, those patents that were sold by target firms receive more new citations than the patents sold by non-target firms in the first and second year after the patent transaction year. We find a similar result in columns 3 and 4 in which an alternative econometric model—the negative binomial model for count data—is used. The evidence indicates that hedge fund activists facilitate the sale of target firms' patents that are not currently efficiently used. The evidence is consistent with the finding reported in Brav, Jiang, and Kim (2013) who find that asset sale associated with hedge fund target exhibits better ex-post performance.

4.2 Redeployment of Human Capital

The second channel we consider is human capital redeployment. If activist hedge funds are able to better allocate human capital after they intervene, they may contribute to the improvement in innovation efficiency as we found in the previous section. To test this conjecture, we undertake a difference-in-differences (DiD) analysis. We first match target and non-target firms based on 2-digit SIC industry and market capitalization. The "intervention" year of the non-target firm is the intervention year of the matched target firm. We then collect individual inventor information from the Harvard Business School (HBS) patent and inventor database available as described in Section 2.1.2. Following Bernstein (2012), we define three groups of inventors: "Stayers", who generate at least one patent both three years before and three years after the intervention year in the same firm; "Leavers", who generate at least one patent in the firm three years before the intervention year and generate at least one patent in a different firm within three years after the intervention year; "New hires", who generate at least one patent in the firm within the first three years after the intervention year and at least one patent in a different firm three years before the event year.

Table 5 reports the DiD results. We compute the DiD estimate by first subtracting the total number of patents per inventor over the thee-year period preceding the intervention from the total number of patents per inventor over the three-year period after the intervention for each target firm. The difference is then averaged over the treatment firm and reported in column (1). By taking this step, we count each firm once regardless of the number of inventors it has. To evaluate the quality of the patents, we first compute the citation ratio per inventor for each target firm by counting the total number of patents it generates three years before (or after) the intervention as well as the total number of citations received by these patents, and dividing the latter by the former. We then calculate the difference in citation ratios before and after the intervention and average it over all target firms. We report this difference in column (1). We repeat the same procedure for non-target firms and report the average change in the total number of patents (citation ratios) surrounding the intervention year in column (2). The DiD estimate is simply the difference in the differences for the target and the non-target firms, and is reported in column (4). We report the t-statistics of the DiD estimates in column (4).

[Insert Table 5 here]

Panel A reports the results for stayers. While it appears that the stayers of both target and non-target firms generate more patents, the increase in target firms is larger, which results in a positive and significant DiD estimate for patent counts. In terms of patent quality, the stayers of target firms produce higher quality patent after the intervention while the stayers of non-target firms produce patents that receive a smaller number of future citations. Hence, the DiD estimate is positive and significant at the 1% level. The evidence suggests that the stayers of target firms become more innovative compared to their counterparts of the non-target firms after hedge fund intervention.

Panel B reports the results for leavers. The DiD estimates for both patent counts and the number of citations per patents are positive and significant, suggesting that the leavers of target firms become more innovative in a new company after they leave the target firm compared to the leavers of non-target firms. The evidence suggests that mobile inventors in firms experiencing hedge fund activism are able to land in places that are a better "fit" compared to leavers in general, possibly a by-product of asset reallocation. A caveat is due here when interpreting our results, however, is that we are unable to claim that the leavers' performance would not have improved had they decided to stay.

Panel C reports the results for new hires. The DiD estimates for both patent counts and the number of citations per patent are positive and significant at the 1% level. This result arises from the a significant improvement in innovation productivity of inventors newly hired by target firms post hedge fund activism and a similar level of innovation productivity of new hires of non-target firms post hedge fund activism. The evidence suggests that the restructuring that target firms undergo subsequent to the entry of activists contributes to the improvement in innovation efficacy of these firms.

5. Linking Reallocation of Innovative Resources to Asset Reallocation Triggered by Activism

The evidence that we document in the previous section linking hedge fund activism with more efficient reallocation of innovation resources (patents and human capital) is intriguing in light of the fact that innovation related issues are not among the common stated objectives of activist hedge funds (see Brav, Jiang, Partnoy, and Thomas (2008) for a description of hedge funds' objectives stated in Schedule 13D as well as in shareholder proposals and public letters). Moreover, activists rarely possess the specific scientific knowledge or technology expertise that is required to guide the innovative process. Addressing the channel of hedge funds' influence will also help gauge the extent to which the effects we document are causal. Since the cumulative evidence in the existing literature indicates that hedge funds have a causal effect on the asset reallocation (see a summary in Brav, Jiang, and Hyunseob (2013)), we proceed to demonstrate the effect of hedge fund activism on innovation efficiency by linking the human capital redeployment to the asset reallocation triggered by hedge fund activism.

To assess whether asset reallocation is accompanied by human capital redeployment (inventor departures), we merge our patent and inventor data with information about asset reallocation. More specifically, we consider two forms of asset reallocation. The first is a target firm's attrition from the Compustat database (*Attrition*), which could be due to an acquisition, going private, or liquidation. All these forms of delisting should be associated with major asset restructuring. The second form is more focused on divestitures (*Divestiture*), defined as divestment of assets more than 10% of the total assets of the target firm. The data source for divestiture is Thomson Reuters SDC Platinum.

For all firms targeted by hedge funds, we estimate the following model:

$$Ln(\#Leavers)_i = \alpha + \beta AssetsReallocation_i + \gamma' Controls_{i,t} + Year_t + Industry_j + \varepsilon_i, \qquad (4)$$

where i indexes firm and j indexes industry. The dependent variable is the natural logarithm of the number of inventors that leave the firm with the first three years after hedge fund activism. The key independent variables are the attrition dummy that equals one if the firm disappears two years after the intervention and zero otherwise, and the divesture dummy that equals one if a divesture event occurs in the year and zero otherwise. Controls include firm size and age. We include both year and industry fixed effects to absorb time- and industry-specific unobservables. Robust standard errors are reported.

We report the results estimating equation (4) in panel A of Table 6. We use the firm's market capitalization as a proxy for firm size and the results are robust to using firm assets as a proxy for size. The coefficient estimates on both the *Attrition* and *Divesture* dummy are positive and significant in columns 1 and 2. The economic effect is also sizable. For example, according to column 2, a divesture is associated with a roughly 14% increase in the number of leavers.

[Insert Table 6 here]

Next, we restrict to divestitures that are directly prompted by hedge funds based on public information. First, in column (3) we define the divesture dummy to be one if the divesture takes place after hedge funds openly push for an asset sale. More specifically, we retrieve this information from Item 4 ("Purpose of Transaction") of the Schedule 13D filings and public letters where the hedge funds state such objectives including the sale of the whole or part of the firm and refocusing of the business strategy. The coefficient estimate on the *Divesture* dummy is positive but insignificant. In column 4, we further restrict the classification to divestures prompted by the hedge fund despite managerial resistance by interacting the hedge fund proposed divestiture with an openly "hostile" stance of the activism. Open confrontation between the activists and firm management indicates that actions proposed by hedge funds face resistance from the management and therefore are unlikely to happen if it were not for the persistence of the activists. In this specification, the coefficient estimate on *Divesture* dummy is positive and significant, suggesting that if the hedge funds have specific agenda and impose the changes despite resistance from firm managers, asset sales have an economically stronger effect on human capital redeployment.

We use the same set-up to examine the relation between asset sales and patent sales. While we show in Table 4 that hedge fund activism helps to better reallocate the intellectual property of a firm by selling undervalued patents, it is not clear whether patent sales is a by-product of asset sales. We report in Table 6, panel B, estimates based on the specification in equation (4) by replacing the dependent variable with the natural logarithm of the number of patents sold within the first three years post interventions. The key variable of interest, *Divestiture*, is defined as divestment of assets more than 10% of the total assets of the firm. We proxy for firm size by market capitalization and book value of assets in columns 1 and 2, respectively. The coefficient estimates on *Divesture* dummy are positive and significant in both columns, suggesting that asset sales are positively associated with the number of patents being sold. The economic effect is quite large. According to column 2, an asset sale is related to 24.2% more patents being sold by the target firm.

6. Conclusion

In this paper, we study the effect of hedge fund activists on corporate innovation. We find that while target firms' R&D spending drops significantly within three years after the intervention by hedge funds, their innovation output remains stable and even exhibits a higher level. The evidence suggests that target firms' innovation efficiency improves after the intervention by hedge funds. We identify two plausible underlying mechanisms through which hedge fund activists improve target firms' innovation efficiency. First, hedge fund activists are able to better reallocate innovative resources in the target firms. Second, the structural changes associated with the entry of activists leads to the redeployment of human capital which is crucial to the innovation process. 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.

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Table 1: Summary Statistics

This table reports the summary statistics of the sample. Panel A reports the characteristics of hedge fund target firms benchmarked against a set of non-target firms. Columns 1-3 report the median, mean, and standard deviation of the characteristics for the target firms. Columns 4-6 report the average difference between the sample firms and industry/size/book-to-market matched firms, the t-statistics for the average difference, and the Wilcoxon signed rank statistics for the median difference. Size matching is dropped for the MV comparisons, and book-to-market matching is dropped for Tobin's Q analysis. Panel B reports the proportion of target firms that falls into each of the quintile groups formed by the CRSP/Compustat universe if the variable is non-negative and the proportion of firms if the variable equals zero.

Panel A: Characteristics of target firms

Variable	Median	Mean	S.D.	Average Difference	t-stat of Difference	Wilcoxon
RNDAssets	0	0.048	0.19	-0.001	-0.42	-2.32
Patent	0	1.723	9.072	-0.289	-1.27	0.91
Citesperpat	0	1.535	5.71	-0.097	-0.57	0.95
Generality	0	0.02	0.087	0.001	0.43	0.78
Originality	0	0.057	0.159	0.009	1.91	2.44
MV	100.58	576.16	893.64	-1.878	-5.92	-0.75
ROA	0.077	0.023	0.299	0.02	2.37	1.61
PPEAssets	0.155	0.241	0.232	-0.007	-1.29	0.89
Leverage	0.207	0.267	0.306	0.027	3.17	3.43
CapexAssets	0.031	0.054	0.069	-0.004	-2.1	-1.48
Tobin Q	1.381	2.397	4.46	-1.452	-8.11	-7.91

Panel B: Characteristics of target firms benchmarked to Compustat quintiles

Variable	% in Var=0	% in Q1	% in Q2	% in Q3	% in Q4	% in Q5
RNDAssets	0.557	0.167	0.084	0.064	0.072	0.056
	(0.741)	(0.052)	(0.052)	(0.052)	(0.052)	(0.052)
Patent	0.765	0.049	0.059	0.055	0.049	0.023
	(0.870)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Citesperpat	0.793	0.081	0.032	0.034	0.032	0.029
	(0.888)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Generality	0.854	0.070	0.018	0.020	0.019	0.019
	(0.926)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Originality	0.810	0.075	0.027	0.028	0.030	0.030
	(0.899)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
MV		0.269	0.200	0.214	0.201	0.116
	--	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
ROA		0.230	0.167	0.199	0.209	0.195
	--	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
PPEAssets		0.224	0.189	0.220	0.208	0.159
	--	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
Leverage		0.279	0.166	0.182	0.185	0.188
	--	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
CapexAssets		0.262	0.198	0.203	0.173	0.164
	--	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)
Tobin Q		0.366	0.173	0.174	0.175	0.112
	--	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)

Table 2: Dynamics of Inputs to Target Firms' Innovation

The table reports regression results documenting the evolution of inputs to innovation around hedge fund intervention. The dependent variables are R&D expenditures and R&D expenditures scaled by firm assets. The key independent variables are a set of firm-year dummy variables, *d[t-3],…, d[t+3],* that correspond to firm-year observations from three years before to three years after a firm is targeted by a hedge fund activist. Control variables include the natural logarithm of firm market capitalization and firm age. Columns (1) and (3) control for industry fixed effects and Columns (2) and (4) control for firm fixed effects. Year fixed effects are included in all columns. t-statistics based on standard errors adjusted for sample clustering at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) $ R&D	(2) $ R&D	(3) R&D/Assets	(4) R&D/Assets
t-3	-22.929**	12.626**	-0.002	-0.001
	(-2.322)	(2.308)	(-0.884)	(-0.995)
t-2	-15.861*	9.725*	-0.000	-0.000
	(-1.711)	(1.658)	(-0.266)	(-0.200)
t-1	-2.782	5.792	-0.000	-0.000
	(-0.279)	(0.906)	(-0.088)	(-0.172)
t	8.363	2.805	-0.001	-0.001
	(0.839)	(0.392)	(-0.471)	(-0.682)
t+1	3.753	-4.577	-0.002	-0.002
	(0.341)	(-0.598)	(-0.932)	(-1.398)
t+2	-13.544	-12.602	-0.002	-0.003
	(-1.084)	(-1.501)	(-0.915)	(-1.416)
t+3	-28.919**	-20.196**	-0.002	-0.003
	(-1.982)	(-2.414)	(-0.921)	(-1.419)
Ln(MV)	108.784***	6.417***	-0.004***	-0.010***
	(20.393)	(2.656)	(-15.620)	(-21.614)
Ln(Firm Age)	94.260***	-12.410**	-0.005***	0.004***
	(14.330)	(-2.436)	(-9.882)	(7.726)
Constant	-605.226***	326.668***	0.079***	0.085***
	(-15.680)	(14.191)	(35.192)	(27.399)
Industry FE	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	122,284	122,284	122,281	122,281
R-squared	0.288	0.898	0.435	0.828
F-test for differences:				
[t+3] - t	9.83	13.6	0.35	0.61
(p-value)	0.002	<0.001	0.556	0.436

Table 3: Dynamics of Outputs From Target Firms' Innovation

We report regression results documenting the evolution of outputs from target firm innovation around hedge fund intervention. The dependent variables are the natural logarithm of one plus patent counts, the natural logarithm of one plus citations per patent, patent generality scores, and patent originality scores. The key independent variables are a set of firm-year dummy variables, *d[t-3],…, d[t+3],* that correspond to firm-year observations from three years before to three years after a firm is targeted by a hedge fund activist. Control variables include the natural logarithm of firm market capitalization and firm age. Columns (1) to (4) control for industry fixed effects and Columns (5) and (8) control for firm fixed effects. Year fixed effects are included in all columns. T-statistics based on standard errors adjusted for sample clustering at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1) Ln(1+#Patents)	(2) Ln(1+#cites per patent)	(3) Generality	(4) Originality	(5) Ln(1+#Patents)	(6) Ln(1+#cites per patent)	(7) Generality	(8) Originality
t-3	0.003	0.030	0.002	0.002	0.033**	0.010	0.000	0.001
	(0.097)	(1.073)	(0.899)	(0.938)	(2.128)	(0.663)	(0.401)	(0.416)
t-2	0.015	0.036	0.002	0.002	0.030*	0.012	-0.000	-0.000
	(0.546)	(1.429)	(1.258)	(1.075)	(1.901)	(0.787)	(-0.244)	(-0.341)
t-1	0.034	0.044*	0.002	0.003	0.023	0.016	-0.001	-0.001
	(1.243)	(1.814)	(1.214)	(1.418)	(1.387)	(1.045)	(-0.705)	(-0.675)
t	0.056**	0.052**	0.002	0.002	0.018	0.018	-0.001	-0.001
	(1.985)	(2.187)	(1.470)	(1.157)	(1.062)	(1.178)	(-0.783)	(-1.008)
t+1	0.071**	0.079***	0.003**	0.004*	0.019	0.024	-0.001	-0.001
	(2.271)	(3.025)	(2.244)	(1.851)	(1.100)	(1.491)	(-0.708)	(-0.997)
t+2	0.078**	0.110***	0.004***	0.005**	0.016	0.025	-0.001	-0.001
	(2.205)	(3.843)	(2.871)	(2.276)	(0.885)	(1.578)	(-0.767)	(-0.909)
t+3	0.070*	0.108***	0.004**	0.005*	0.021	0.024	-0.001	-0.000
	(1.705)	(3.271)	(2.449)	(1.953)	(1.177)	(1.450)	(-0.658)	(-0.323)
Ln(MV)	0.283***	0.146***	0.010***	0.012***	0.010**	0.010***	0.002***	0.002***
	(37.041)	(31.598)	(30.392)	(31.804)	(2.349)	(2.667)	(7.121)	(5.124)
Ln(Firm Age)	0.312***	0.210***	0.001	-0.004***	0.083***	0.072***	-0.004***	-0.004***
	(27.468)	(25.894)	(1.490)	(-6.910)	(8.991)	(9.782)	(-9.068)	(-5.753)
Constant	-1.417***	-0.772***	-0.041***	-0.023***	0.933***	0.505***	0.024***	0.044***
	(-25.910)	(-23.776)	(-20.317)	(-9.770)	(23.396)	(15.829)	(12.030)	(15.985)

	(1) Ln(1+#Patents)	(2) Ln(1+#cites per patent)	(3) Generality	(4) Originality	(5) Ln(1+#Patents)	(6) Ln(1+#cites per patent)	(7) Generality	(8) Originality
Industry FE	Yes	Yes	Yes	Yes	No	No	No	No
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	122,284	122,284	122,284	122,284	122,284	122,284	122,284	122,284
R-squared	0.495	0.386	0.295	0.318	0.949	0.909	0.907	0.910
F-test for differences:								
[t+3] - t	0.18	5.05	2.84	1.71	0.06	0.13	0.01	0.44
(p-value)	0.673	0.025	0.092	0.191	0.812	0.719	0.957	0.508

Table 4: Patent Transactions

This table reports the regression results estimating the dynamics of patent citations around patent transactions. The dependent variable is the number of new citations a patent receives in a given year. The key independent variables are the interaction terms of the target dummy and event year dummies, where the target dummy equals one if the firm is a hedge fund target firm and zero otherwise and the event year dummy equals one if the calendar year is *t* years before (after) the patent transaction year (where $t = 0, 1, 2, 3$) and zero otherwise. Columns 1 and 2 control for patent fixed effects. Columns 3 and 4 control for patent technology class fixed effects. Calendar year fixed effects are included in all columns. Columns 1 and 2 provide OLS regression results, and columns 3 and 4 provide Negative Binomial model regression results. Columns 1 and 3 require that the patent transactions occur after the hedge fund intervention year, and columns 2 and 4 require that the patent transactions occur within the first five years after the hedge fund intervention year. T-statistics based on standard errors adjusted for sample clustering at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Model	OLS	OLS	Negative Binomial	Negative Binomial
Dependent variable	New Cites	New Cites	New Cites	New Cites
*Target * year b3*	0.059	0.056	-0.094***	-0.069***
	(1.29)	(1.14)	(-4.02)	(-2.68)
*Target * year b2*	0.023	0.027	-0.051*	-0.058*
	(0.50)	(0.52)	(-1.93)	(-1.95)
*Target * year b1*	0.027	-0.016	-0.041	-0.032
	(0.053)	(-0.29)	(-1.57)	(-1.16)
*Target * year 0*	0.086	0.079	-0.033	-0.010
	(1.55)	(1.24)	(-1.44)	(-0.32)
*Target * year a1*	0.138**	0.143*	0.020	0.035
	(2.24)	(1.94)	(0.55)	(0.94)
*Target * year a2*	0.144**	0.146*	0.087**	0.099***
	(2.11)	(1.76)	(2.42)	(2.68)
*Target * year a3*	-0.002	-0.054	0.036	0.031
	(-0.004)	(-0.64)	(0.89)	(0.74)
Year b3	-0.038***	-0.038***	0.061***	0.061***
	(-5.13)	(-5.12)	(11.65)	(11.64)
Year b2	-0.043***	-0.043***	0.058***	0.058***
	(-6.03)	(-6.02)	(11.49)	(11.48)
Year b1	-0.038***	-0.038***	0.054***	0.054***
	(-5.37)	(-5.36)	(10.90)	(10.90)
Year 0	-0.017**	-0.019**	0.062***	0.062***
	(-2.38)	(-2.38)	(12.15)	(12.15)
Year a1	-0.037***	-0.037***	0.043***	0.043***
	(-5.24)	(-5.24)	(8.62)	(8.62)

	(1)	(2)	(3)	(4)
Model	OLS	OLS	Negative Binomial	Negative Binomial
Dependent variable	New Cites	New Cites	New Cites	New Cites
Year a2	-0.042***	-0.042***	0.036***	0.036***
	(-6.38)	(-6.37)	(7.39)	(7.39)
Year a3	-0.033***	-0.033***	0.033***	0.033***
	(-5.14)	(-5.14)	(6.52)	(6.51)
Ln(Patent age)	-0.013**	-0.013**	-0.362***	-0.362***
	(-2.48)	(-2.52)	(-220.00)	(-221.95)
Constant	1.833***	1.833***	-1.188***	-1.188***
	(40.10)	(40.09)	(-15.82)	(-15.80)
Year FE	Yes	Yes	Yes	Yes
Patent FE	Yes	Yes	No	No
Tech class FE	No	No	Yes	Yes
Log pseudo likelihood			-13,086,889	-13,077,687
Observations	9,269,424	9,264,298	9,268,993	8,887,520
R-squared	0.503	0.503		

Table 5: Inventor Turnover

This table reports difference-in-differences results for inventor turnover around hedge fund interventions. Matched non-target firms are selected from all publicly traded non-target firms that are in the same 2-digit SIC industry with the closest market capitalization. The "event year" for the non-target firm is the intervention year of the corresponding target firm. Panel A reports results for inventor stayers who generate at least one patent both before and after the event year in the same firm. Panel B reports the results for inventor leavers who generate at least one patent in the target firm before the event year and generate at least one patent in a different firm after the event year. Panel C reports the results for new hires who generate at least one patent in a different firm before the event year and at least one patent in the target firm after the event year. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Stayers

	Target (After-Before)	Non-Target (After-Before)	Diff-in-Diff	t-stat
	(1)	(2)	(3)	(4)
Number of patents	0.17	0.02	0.15***	2.68
Citations per patent	1.77	-1.11	2.88***	3.33

Panel B: Leavers

	Target (After-Before)	Non-Target (After-Before)	Diff-in-Diff	t-stat
Number of patents	0.14	-0.03	0.16**	2.39
Citations per patent	2.37	-0.02	2.39***	2.75

Panel C: New Hires

	Target (After-Before)	Non-Target (After-Before)	Diff-in-Diff	t-stat
Number of patents	0.27	-0.06	0.33***	6.24
Citations per patent	4.71	0.21	4.50***	5.34

Table 6: Patent Transactions and Human Capital Redeployment

This table reports the relation between capital reallocation and human capital redeployment as well as patent transactions. The dependent variable in Panel A is the natural logarithm of the total number of inventors leaving the firm within three years after hedge fund interventions. The key independent variables are the attrition dummy that equals one if the firm is disappears in two years and zero otherwise, and a divesture dummy that equals one if a divesture event occurs in the year and zero otherwise. The divesture dummy in column 3 represents divestitures prompted by hedge funds and the divesture dummy in column 4 represents hedge fund prompted divestures despite managerial resistance. The dependent variable in Panel B is the natural logarithm of the total number of patents sold within the first three years after hedge fund interventions. Control variables include firm size, the natural logarithm of firm age, year fixed effects and industry fixed effects. T-statistics based on standard errors adjusted for sample clustering at the firm level are displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Number of leavers

	(1) Ln(1 + # leavers)	(2) Ln(1 +# leavers)	(3) Ln(1 +# leavers)	(4) Ln(1 +# leavers)
Attrition	0.094*			
	(1.816)			
Divesture dummy		0.143***	0.080	0.184*
		(2.896)	(0.920)	(1.717)
Ln(MV)	0.074***	0.064***	0.068***	0.067***
	(5.493)	(6.517)	(6.944)	(6.852)
Ln(Age)	0.038*	0.034**	0.036**	0.035**
	(1.794)	(2.254)	(2.426)	(2.333)
Constant	-0.199	-0.683	-0.711	-0.701
	(-0.638)	(-1.225)	(-1.272)	(-1.256)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,505	1,640	1,640	1,640
R-squared	0.178	0.170	0.166	0.167

Panel B: Number of patents sold

	(1) Ln (1 +# of patents sold)	(2) Ln (1 + # of patents sold)
Divesture dummy	0.285***	0.242**
	(2.806)	(2.393)
Ln(MV)	0.127***	
	(6.357)	
Ln(Assets)		0.152***
		(7.684)
Ln(Age)	0.085***	0.071**
	(2.765)	(2.337)
Constant	-1.592	-1.837*
	(-1.421)	(-1.650)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	1,562	1,567
R-squared	0.182	0.192