Financial Management

Hedge Funds and Corporate Innovation

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Using National Bureau of Economics Research patent data and hedge fund holdings in US firms from 1998 to 2006, we examine the effect of hedge fund ownership on corporate innovation. We find that hedge fund ownership increases both patent quantity and quality, even after controlling for endogeneity. Hedge funds appear to increase innovation and firm value by increasing research and development (R&D) productivity and innovation efficiency rather than R&D input. Our study suggests another channel through which hedge funds may enhance firm value, contributing to the literature on hedge fund ownership.

The contribution of our paper is to document that hedge fund ownership of a company increases corporate innovation. Our findings offer new insights into the controversial role of hedge funds in corporate innovation. Academics, policy makers, and practitioners have long been concerned that the short-term focus and frequent trading of hedge funds, whose preference is to deliver short-term gains to their clients in order to attract more fund inflows, might pressure corporate managers to underinvest in long-term intangible projects, such as research and development (R&D) and innovation, in order to meet short-term earnings goals (Graves and Waddock, 1990; Jacobs, 1991; Porter, 1992; Bushee, 1998). This myopic investment behavior by corporate managers has been argued to undermine competitiveness and stifle technological innovation (Jacobs, 1991). However, it is plausible that hedge funds may also be a solution to this myopia problem. The sophistication and concentrated ownership of hedge funds can mitigate the free rider problem associated with shareholder activism and allow them to monitor corporate managers more effectively, thus promoting innovation and enhancing long run firm value (Rubin, 2007; Brav et al., 2008; Edmans, 2009; Klein and Zur, 2009).

Using a sample of hedge fund holdings in US firms and National Bureau of Economic Research (NBER) patent data from 1998 to 2006, we examine the effect of hedge fund ownership on corporate innovation. We document a statistically and economically significant positive relation between hedge fund ownership and a firm's future patent quantity and quality as proxied by the number of patents, citation intensity, a generality measure that captures how broadly the patent impacts future descendants, and an originality measure that proxies for how original the patent is relative to its predecessors. For instance, a 1*SD* increase in hedge fund holdings (i.e., 10.62%) is associated with an increase of 3.6% to 6.2% (3.6% to 7.5%) in patent count (citations), and an increase of 6.7% to 7.5% (roughly 4.4%) in generality (originality).

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While our results suggest a positive effect of hedge fund ownership on innovation, they are also consistent with two alternative explanations. First, the positive association may be driven by other unobservable factors correlated with both hedge fund ownership and innovation. In addition, hedge funds may choose, ex ante, to invest in firms with greater potential for successful innovation. While using firm fixed effects mitigates endogeneity arising from firm-specific, time-invariant, omitted variables, we employ three additional tests to further address the endogeneity issue. First, we conduct change-on-change regressions. Second, we construct two instrumental variables, namely an S&P 500 inclusion dummy and the state-level intensity of hedge fund ownership, and undertake a two-stage least squares/instrumental variable (2SLS/IV) analysis. Finally, we follow Wintoki, Linck, and Netter (2012) and apply a dynamic panel generalized method of moments (GMMs) estimation. Our results remain robust after controlling for endogeneity.

Overall our findings suggest that hedge fund ownership promotes both patent quantity and quality. This effect is stronger when hedge funds collectively have larger holdings (i.e., blockholdings) in the firm and, as such, more effectively influence corporate managers' decisions, and when hedge fund ownership in the firm constitutes a larger proportion of total assets under management by the fund.

We then investigate the underlying mechanism through which hedge funds affect innovation. Hedge funds appear to promote innovation primarily by enhancing R&D productivity and innovation efficiency rather than increasing R&D input. Prior literature suggests three channels through which hedge funds may enhance innovation efficiency. First, hedge funds may motivate their portfolio firms to alter the composition of R&D programs by allocating more resources to innovative, productive, and high quality projects, while reducing unproductive and marginal R&D (Almeida, Hsu, and Li, 2013). Additionally, hedge funds may learn from the patenting experiences and innovation expertise of firms in their investment portfolios and facilitate knowledge diffusion among them, thereby enhancing both innovation quantity and quality of those firms (Gonzalez-Uribe, 2013). Finally, Aghion, Reenen, and Zingales (2013) find that institutional investors have only a small positive effect on R&D, but a large positive effect on patenting innovation, suggesting that the main effect of ownership is to alter quality and/or productivity of R&D rather than stimulate more R&D input.

To provide further evidence concerning the mechanism, we explore cross-sectional heterogeneity. The positive effect of hedge fund ownership on innovation efficiency is stronger when firms are more innovative and innovation efficiency is more crucial for success. Specifically, this occurs when firms are subject to greater financial constraints (e.g., smaller free cash flow and higher leverage) and increasing innovation efficiency rather than input is more important and relevant (Almeida et al., 2013); when managerial myopia is more severe in undervalued (lower Q) firms (Aghion et al., 2013); and when firms operate in more competitive industries where productivity and efficiency are critical (Brav, Jiang, and Kim, 2013). Taken together, hedge fund ownership appears to benefit innovation by increasing efficiency and reducing excessive investments in unproductive R&D. Consequently, hedge fund ownership increases firm value via a positive effect on innovation, suggesting an additional channel through which hedge funds can add firm value.

Our paper adds to the literature regarding hedge funds and their effect on corporate decision-making in that we find a positive effect of hedge fund ownership on corporate innovation. The heightened financial incentives, sophistication, light regulation, concentrated ownership, and unique structure (e.g., lock-up provisions) of hedge funds allow them to effectively monitor corporate managers and promote innovation. Indeed, recent work indicates that hedge funds are effective monitors who bring about operational, financial, and governance improvement in target firms (Clifford, 2008; Brav, Jiang, and Kim, 2009; Klein and Zur, 2009; Huang, 2010; Brav et al., 2013). We also contribute to a nascent literature on patent innovation by providing the first empirical evidence that hedge fund ownership enhances innovation quantity, quality, and efficiency, and subsequently increases firm value.[1]

The remainder of the paper proceeds as follows. Section I describes the data. Section II examines the effect of hedge fund ownership on patent quantity and quality. Section III investigates the mechanism through which hedge fund ownership affects innovation. Section IV explores the relationship between innovation, hedge fund holdings, and firm value. We present our conclusions in Section V.

I. Data

We obtain patents and patent citations data from the NBER patent database compiled by Hall, Jaffe, and Trajtenberg (2002), and hedge fund ownership data from the Thomson Reuters Institutional Holdings (13F) database. Firm financial information is obtained from Compustat and stock return data from the Center for Research in Security Prices (CRSP). The sample period begins in 1998, when hedge fund holdings data are available, and ends in 2006 when the NBER patent data end.[2] Our sample contains all firm-year observations in Compustat during our sample period that have nonmissing hedge fund holdings data. To mitigate sample selection bias, we follow Atanassov (2013) and He and Tian (2013) and assign zero value to firm-years with missing patent or R&D data and include them in our regressions.

A. Patent Measures

To measure corporate innovation, we follow Trajtenberg, Henderson, and Jaffe (1997), Hall et al. (2002), and Hall (2005) and employ a variety of metrics including the number of patents filed per year (*PAT*), the number of citations received per patent (*Cite*), patent generality (*GEN*) that captures how broadly the patent impacts future descendants, and patent originality (*ORG*) that measures how original the patent is relative to its predecessors. To control for industry trend and truncation bias in patent data, we also use bias-adjusted measures of patent quantity (*PAT_tn* and *PAT_tc*), citations (*Cite_tn*, *Cite_tc*, and *Cite_h*), generality (*GEN_tn* and *GEN_tc*), and originality (*ORG_tn* and *ORG_tc*). Appendix A provides details regarding these patent measures. The definitions of these measures are also summarized in Panel A of Appendix B.

B. Hedge Fund Ownership

Since 1978, all institutions with more than $100 million under management are required to file 13F forms quarterly for all US equity positions worth over $200,000 or consisting of more than 10,000 shares. These reporting requirements apply regardless as to whether an institution is regulated by the Securities and Exchange Commission (SEC) or not. Thus, they also apply to

[1] Prior research has examined the relation between innovation and various other factors, including stock returns (Hsu, 2009; Li, 2011; Hirshleifer, Hsu, and Li, 2013; Almeida et al., 2013), market liquidity (Fang, Tian, and Tice, 2013), leverage buyouts (Lerner, Sorensen, and Stromberg, 2011), state anti-takeover laws (Atanassov, 2013), corporate governance (Chemmanur and Tian, 2013), analyst coverage (He and Tian, 2013), institutional ownership (Aghion et al., 2013), bank loan contracting (Francis, Hasan, Huang, and Sharma, 2012), bank competition (Cornaggia, Mao, Tian, and Wolfe, 2015), chief executive officer (CEO) overconfidence (Hirshleifer, Low, and Teoh, 2012), non-executive employee stock options (Chang, Fu, Low, and Zhang, 2015), labor unions (Bradley, Kim, and Tian, 2013), and board interlocks (Helmers, Patnam, and Rau, 2013), among others.

[2] Since we estimate lead-lag regressions in our main tests, our dependent (independent) variables cover the period from 1999 to 2006 (1998-2005).

hedge fund firms whose holdings of US stocks exceed the specified thresholds.[3] The advantage of using the 13F data set is that it does not suffer from the selection bias inherent in commercial hedge fund databases to which hedge funds voluntarily provide this information. However, a limitation of the 13F data set is that it does not cover the short positions or derivatives. As such, our analysis is based upon the long side of equity portfolios.

Since the 13F database does not identify hedge fund managers, we retrieve hedge fund manager information from several sources, including the Lipper/TASS, Morningstar, and Center for International Securities and Derivative Markets (CISDM) hedge fund databases. We match each candidate hedge fund by name with the 13F database. Our matching process follows the approach of Brunnermeier and Nagel (2004) and Griffin and Xu (2009).

Panel B of Appendix B provides definitions of hedge fund ownership. Hedge fund holdings (*HFH*) in a firm at the year-end are defined as the sum of shares held by the sample hedge funds divided by the total number of shares outstanding for the firm. ΔHFH denotes the annual change in *HFH* from the previous year-end.

C. Summary Statistics

Table I presents descriptive statistics on patent measures, hedge fund ownership, and control variables from 1998 to 2006. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. While we assign zero to missing patent measures in our multivariate regression analysis to mitigate sample selection bias, we report the summary statistics of raw patent data. This is due to the concern that a majority of zero may occur in our regression sample for some patent measures, thus providing little insight into the data. To compare with the extant literature, however, we assign zero to missing R&D and include the observations in our summary statistics.

Panel A shows that within the sample of firms having at least one patent in any calendar year, an average firm files 29 patents per year (which are ultimately granted). However, the median is only three, suggesting that patent quantity is highly skewed and concentrated within a small number of innovative firms. After correcting for truncation bias and time lag in the patent application process, an average (median) firm files 6.57 (1.00) patents per year in the case of *PAT_tn* and 1.89 (0.26) patents per year in the case of *PAT_tc*. A patent receives, on average (at the median), 2.50 (1.00) citations by future patents. After adjusting for application time and industry, an average (median) patent receives 9.16 (4.99) citations in the case of *Cite_h*, 1.08 (0.76) citations in the case of *Cite_tn*, and 1.03 (0.66) citations for *Cite_tc*. The average (median) generality is 0.31 (0.25) for *GEN*, 0.60 (0.51) for *GEN_tn*, and 0.62 (0.52) for *GEN_tc*. The average (median) *ORG* score is 0.53 (0.54), *ORG_tn* is 1.15 (1.12), and *ORG_tc* is 1.03 (1.05). All of these numbers are consistent with the prior literature (Hall et al., 2002; Lerner, Sorensen, and Stromberg, 2011; Chemmanur and Tian, 2013).

Panel B demonstrates that for firms with nonmissing hedge fund ownership data, on average, 9.5% of their shares outstanding are held by hedge fund firms. The median value is 6.3%. The mean (median) change over one year in hedge fund ownership is 1.8% (0.5%). Panel C indicates that all of the control variables are consistent with the literature. For example, an average (median) firm has total assets of $5.3 billion ($380 million), total sales of $2.3 billion ($209 million), an R&D to assets ratio of 4.3% (0.0), a capital expenditures to total assets ratio of 5.6% (3.5%), ROA of 2.3% (9.5%), a leverage ratio of 22.3% (16.7%), Tobin's q of 2.2 (1.5), and an age of

[3] The SEC website provides detailed information regarding these reporting requirements at www.sec.gov/divisions/investment/13ffaq.htm.

Table I. Summary Statistics

This table provides summary statistics of innovation measures from 1999 to 2006, and hedge fund holdings and control variables from 1998 to 2005. The full sample contains all available Compustat firms. The patent and hedge fund holdings data exclude observations with missing values. R&D is assigned a value of zero if missing. All variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels.

Variable	*N*	Mean	*SD*	Q25	Median	Q75
			Panel A. Innovation Measures (1999-2006)			
PAT	11,013	29.206	98.346	1.000	3.000	12.000
PAT_tn	11,013	6.566	20.403	0.392	1.000	3.329
PAT_tc	11,013	1.887	6.005	0.098	0.262	0.879
Cite	11,013	2.504	4.732	0.000	1.000	3.000
Cite_h	11,013	9.156	13.600	0.000	4.991	12.146
Cite_tn	10,763	1.083	1.370	0.000	0.760	1.403
Cite_tc	10,934	1.026	1.392	0.000	0.661	1.359
GEN	6,561	0.305	0.267	0.080	0.250	0.462
GEN_tn	6,529	0.602	0.512	0.186	0.513	0.895
GEN_tc	6,556	0.615	0.522	0.185	0.520	0.909
ORG	10,824	0.534	0.219	0.411	0.544	0.684
ORG_tn	10,091	1.154	0.580	0.837	1.118	1.417
ORG_tc	10,824	1.033	0.423	0.803	1.052	1.317
			Panel B. Hedge Fund Holdings (1998-2005)			
HFH	38,288	0.095	0.106	0.011	0.063	0.141
ΔHFH	30,075	0.018	0.069	−0.008	0.005	0.040
			Panel C. Control Variables (1998-2005)			
AT ($mn)	81,762	5,285	21,922	81	380	1,733
MV ($mn)	79,593	2,538	8,825	55	229	1,011
Sales ($mn)	68,225	2,276	7,377	41	209	1,064
RD_AT	93,471	0.043	0.113	0.000	0.000	0.026
RD_Sale	93,471	0.259	1.671	0.000	0.000	0.025
CAPX_AT	67,184	0.056	0.068	0.016	0.035	0.069
PPENT_AT	80,299	0.226	0.241	0.034	0.133	0.343
ROA	67,277	0.023	0.294	0.001	0.095	0.155
LEV	80,602	0.223	0.229	0.024	0.167	0.346
CASH_AT	68,247	0.212	0.240	0.030	0.111	0.319
Q	67,959	2.202	2.346	1.082	1.462	2.319
HI	90,500	0.219	0.225	0.060	0.151	0.296
HI2	90,500	0.099	0.200	0.004	0.023	0.087
AGE	93,471	12.683	13.535	4.000	8.000	17.000

12.7 (8) years since being listed in CRSP. Table II reports that R&D (innovation input) and patent (innovation output) measures are positively correlated with each other.

II. Hedge Fund Ownership and Innovation

This section examines the effect of hedge fund ownership on innovation. Section IIIA reports the baseline regression results. Sections IIB, IIC, and IID address the endogeneity issue via

Table II. Correlation Coefficients of Patent and R&D

This table presents Pearson correlation coefficients among R&D (innovation input) and patent (innovation output) measures. The sample contains 33,048 firm-year observations from 1998 to 2006 that are used in our main regression analysis. The patent and R&D data are assigned a value of zero if missing. All variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels.

	LnPAT	lnPAT_tn	lnPAT_tc	lnCite	lnCite_h	lnCite_tn	lnCite_tc	GEN	GEN_tn	GEN_tc	ORG	ORG_tn	ORG_tc	RD_AT	RD_Sale
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(2)	0.970***														
(3)	0.912***	0.960***													
(4)	0.572***	0.481***	0.387***												
(5)	0.685***	0.587***	0.480***	0.948***											
(6)	0.626***	0.546***	0.451***	0.833***	0.912***										
(7)	0.631***	0.551***	0.463***	0.854***	0.923***	0.967***									
(8)	0.374***	0.304***	0.229***	0.800***	0.735***	0.636***	0.643***								
(9)	0.394***	0.321***	0.248***	0.807***	0.749***	0.654***	0.668***	0.979***							
(10)	0.383***	0.312***	0.237***	0.799***	0.743***	0.655***	0.664***	0.994***	0.986***						
(11)	0.689***	0.598***	0.468***	0.579***	0.662***	0.614***	0.603***	0.467***	0.468***	0.472***					
(12)	0.649***	0.547***	0.433***	0.525***	0.619***	0.581***	0.578***	0.403***	0.424***	0.415***	0.879***				
(13)	0.685***	0.596***	0.469***	0.569***	0.651***	0.606***	0.596***	0.456***	0.460***	0.464***	0.997***	0.878***			
(14)	0.134***	0.081***	0.066***	0.123***	0.139***	0.141***	0.124***	0.091***	0.099***	0.096***	0.191***	0.191***	0.195***		
(15)	0.014***	0.002	0.000	0.013**	0.015***	0.020***	0.013**	0.009*	0.012**	0.010**	0.038***	0.051***	0.042***	0.357***	1.000

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

change-on-change regressions, 2SLS/IV regressions, and the dynamic panel GMM estimation, respectively. We then conduct analysis including firms with missing hedge fund ownership in Section IIE. Section IIF examines the impact of hedge fund blockholdings.

A. Baseline Regressions of Innovation on Hedge Fund Ownership

To examine the relationship between hedge fund ownership and subsequent corporate innovation, we employ the following multivariate regression analysis:

$$Innovation_{i,t+1} = \alpha_t + \gamma_i + \beta HFH_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}, \tag{1}$$

where $Innovation_{i,t+1}$ measures innovative activities of firm i in year $t+1$, including various metrics of patent quantity, citations, generality, and originality, $HFH_{i,t}$ refers to hedge fund holdings (*HFH*) in firm i at the end of year t, X contains all of the control variables shown in prior literature to affect innovation, and α_t and γ_i are year and firm fixed effects, respectively. If hedge fund ownership leads to declines in innovation, we expect a negative β. Alternatively, if hedge funds promote innovative activities, a positive β is anticipated.

Following Atanassov (2013) and Chemmanur and Tian (2013), we include firm fixed effects for at least two reasons. First, the inclusion of firm fixed effects enables us to directly test whether and how the variation of hedge fund ownership within a firm is associated with the subsequent variation in innovation. Additionally, our empirical analyses may be subject to endogeneity issues between hedge fund holdings and innovation due to omitted unobservable firm attributes (e.g., the innovation culture of a company) that might drive both hedge fund ownership and innovation jointly. Firm fixed effects can mitigate this endogeneity concern arising from unobservable, firm-specific, time invariant, omitted variables.[4]

1. Hedge Fund Ownership and Patent Quantity

Table III presents our baseline regression results of innovation on hedge fund holdings (*HFH*). We begin with patent quantity measures in Models 1–3 of Panel A. To account for the skewness of patent quantity measures as demonstrated in Table I, the dependent variables are, respectively, the natural logarithm of one plus the total number of patents filed by (and ultimately granted to) a firm during calendar year $t+1$ (*LnPAT*), and the natural logarithm of one plus the bias-adjusted patent quantity, *LnPAT_tn* and *LnPAT_tc*. The t-statistics (in parentheses) are corrected for firm-level clustering. We find that *HFH* is significantly and positively related to all patent quantity measures. Specifically, a 1*SD* increase in *HFH* (10.62% for the baseline regression sample of 33,048 observations, untabulated) is associated with an increase of 1.78 (*LnPAT*), 1.25 (*LnPAT_tn*), and 0.89 (*LnPAT_tc*) percentage points. Given the baseline sample mean (untabulated) of 0.50 (*LnPAT*), 0.28 (*LnPAT_tn*), and 0.14 (*LnPAT_tc*), these changes translate into economically significant increases of 3.6%, 4.4%, and 6.2%.

The coefficient estimates for control variables are consistent with previous studies (Chemmanur and Tian, 2013; He and Tian, 2013). Firm size is positive, consistent with larger firms being more capable of generating greater in-house R&D and innovation due to greater resources, more human capital, less takeover threats, and more flexibility in business operations. The R&D to sales ratio is insignificant and the capital expenditures to assets ratio is negative. However, untabulated

[4] As suggested by Zhou (2001), the inclusion of firm fixed effects may significantly reduce the power of statistical tests, especially in the absence of large within variations in ownership, and thus should, if anything, bias against finding significant results.

Table III. Baseline Regressions of Innovation on Hedge Fund Holdings

This table presents baseline regression results of corporate innovation on hedge fund holdings (HFH), where innovation is measured by patent quantity and citations in Panel A, and patent generality and originality in Panel B. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. Firm and year fixed effects are included in all of the models. *t*-Statistics (in parentheses) are corrected for firm-level clustering.

Panel A. Patent Quantity and Citations

	LnPAT	LnPAT_tn	LnPAT_tc	LnCite	LnCite_h	LnCite_tn	LnCite_tc
HFH	**0.168*****	**0.118*****	**0.084*****	**0.117*****	**0.204*****	**0.040**	**0.045***
	(3.14)	**(3.56)**	**(4.41)**	**(3.39)**	**(3.21)**	**(1.39)**	**(1.66)**
LN_MV	0.050***	0.035***	0.019***	−0.021***	−0.015**	0.000	0.000
	(8.15)	(9.30)	(8.65)	(−5.41)	(−2.10)	(0.04)	(0.08)
RD_SALE	−0.000	−0.000	−0.000	0.001	0.001	0.000	0.000
	(−0.37)	(−0.25)	(−0.29)	(1.40)	(1.19)	(0.66)	(1.21)
CAPX_AT	−0.171*	−0.084	−0.067**	−0.082	−0.204*	−0.094*	−0.070
	(−1.89)	(−1.49)	(−2.06)	(−1.41)	(−1.89)	(−1.94)	(−1.52)
PPENT_AT	0.307***	0.171***	0.085***	0.228***	0.396***	0.086**	0.087***
	(4.84)	(4.36)	(3.73)	(5.59)	(5.26)	(2.55)	(2.71)
ROA	0.022	0.005	−0.001	0.068***	0.086***	0.012	0.014
	(0.93)	(0.33)	(−0.12)	(4.62)	(3.16)	(0.99)	(1.23)
LEV	−0.124***	−0.035*	−0.021**	−0.050***	−0.103***	−0.045***	−0.028*
	(−4.17)	(−1.89)	(−1.97)	(−2.59)	(−2.92)	(−2.85)	(−1.88)
CASH_AT	0.043	0.014	−0.009	0.053**	0.120***	0.047**	0.051***
	(1.22)	(0.64)	(−0.72)	(2.31)	(2.85)	(2.50)	(2.84)
Q	0.013***	0.003***	0.002***	0.014***	0.023***	0.005***	0.004***
	(7.07)	(2.79)	(2.91)	(11.56)	(10.42)	(5.47)	(4.72)
HI	−0.029	0.037	0.009	0.310***	0.250*	−0.000	0.047
	(−0.22)	(0.46)	(0.20)	(3.78)	(1.66)	(−0.00)	(0.73)
HI2	0.146	0.004	−0.007	−0.165*	−0.027	0.055	0.007
	(1.08)	(0.05)	(−0.14)	(−1.90)	(−0.17)	(0.76)	(0.10)
LN_AGE	0.072***	0.097***	0.057***	0.013	−0.002	−0.020**	−0.015*
	(4.72)	(10.26)	(10.44)	(1.38)	(−0.10)	(−2.52)	(−1.89)
Intercept	2.132***	1.396***	0.898***	0.327**	0.727***	0.205*	0.249**
	(10.25)	(10.82)	(12.05)	(2.44)	(2.95)	(1.85)	(2.36)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.815	0.833	0.857	0.546	0.574	0.497	0.511
N	33,048	33,048	33,048	33,048	33,048	33,048	33,048

Panel B. Patent Generality and Originality

	GEN	GEN_tn	GEN_tc	ORG	ORG_tn	ORG_tc
HFH	**0.025****	**0.045****	**0.048****	**−0.001**	**0.114****	**−0.006**
	(2.26)	**(2.07)**	**(2.12)**	**(−0.04)**	**(2.55)**	**(−0.18)**
LN_MV	−0.005***	−0.010***	−0.010***	0.007***	0.017***	0.012***
	(−4.32)	(−3.98)	(−3.96)	(3.33)	(3.28)	(3.05)

(Continued)

Table III. Baseline Regressions of Innovation on Hedge Fund Holdings *(Continued)*

Panel B. Patent Generality and Originality

	GEN	GEN_tn	GEN_tc	ORG	ORG_tn	ORG_tc
RD_SALE	0.000	0.000	0.000	0.001**	0.002**	0.001**
	(0.93)	(0.71)	(0.79)	(2.55)	(2.42)	(2.49)
CAPX_AT	−0.019	−0.034	−0.042	−0.015	0.017	−0.018
	(−1.03)	(−0.92)	(−1.10)	(−0.50)	(0.22)	(−0.30)
PPENT_AT	0.046***	0.083***	0.088***	0.047**	0.056	0.085**
	(3.50)	(3.23)	(3.29)	(2.22)	(1.05)	(2.05)
ROA	0.017***	0.026***	0.029***	0.001	0.014	0.001
	(3.55)	(2.76)	(2.99)	(0.07)	(0.74)	(0.04)
LEV	−0.010	−0.021*	−0.022*	−0.020**	−0.060**	−0.041**
	(−1.56)	(−1.74)	(−1.74)	(−2.03)	(−2.41)	(−2.13)
CASH_AT	0.015**	0.031**	0.033**	0.024**	0.060**	0.048**
	(2.10)	(2.14)	(2.18)	(2.03)	(2.02)	(2.05)
Q	0.003***	0.005***	0.006***	0.003***	0.005***	0.005***
	(8.72)	(7.24)	(7.77)	(4.69)	(3.52)	(4.01)
HI	0.081***	0.149***	0.147***	−0.060	−0.088	−0.138*
	(3.10)	(2.91)	(2.73)	(−1.39)	(−0.83)	(−1.66)
HI2	−0.054*	−0.090*	−0.095*	0.093**	0.200*	0.194**
	(−1.92)	(−1.65)	(−1.65)	(2.04)	(1.76)	(2.20)
LN_AGE	0.000	0.005	0.000	−0.020***	−0.016	−0.038***
	(0.14)	(0.75)	(0.04)	(−3.97)	(−1.28)	(−3.85)
Intercept	0.062	0.130	0.129	0.293***	0.489***	0.606***
	(1.45)	(1.55)	(1.47)	(4.19)	(2.80)	(4.46)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.428	0.425	0.423	0.611	0.535	0.608
N	33,048	33,048	33,048	33,048	33,048	33,048

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

results show that the R&D to assets ratio is positive indicating that greater innovation input is associated with greater output. Tobin's q is positive, suggesting that firms with larger growth options generate greater innovations. Finally, patents are negatively related to leverage ratio and positively related to asset tangibility (PPENT_AT) and firm age.

2. Hedge Fund Ownership and Patent Citations

To examine the relationship between hedge fund ownership and the quality of corporate innovation, we analyze various metrics. Patent citations capture the impact of an innovation on its descendants. The more citations a patent receives in the future, the more influence it has on future inventions and the higher social value it generates. The last four columns in Panel A of Table III present the regression results of patent citations. The dependent variables are *LnCite*, *LnCite_h*, *LnCite_tn*, and *LnCite_tc*, respectively. *LnCite* is equal to the natural logarithm of one plus the number of citations received per patent filed (and ultimately granted) in year $t+1$. *LnCite_h* is the natural logarithm of one plus bias-adjusted *Cite* using the quasi-structural method, while *LnCite_tn* and *LnCite_tc* are bias-adjusted using the fixed effects method (Hall et al., 2002).

We find that *HFH* is positively related to citations per patent for all four measures, albeit insignificantly for *LnCite_tn*. Given the baseline sample means (untabulated) of 0.17 (*LnCite*), 0.36 (*LnCite_h*), and 0.13 (*LnCite_tc*), a 1*SD* increase in *HFH* (10.62%) amounts to an increase of 7.5% (*LnCite*), 6.0% (*LnCite_h*), and 3.6% (*LnCite_tc*), respectively, from the sample mean, which are both statistically and economically significant. Our results indicate that higher hedge fund ownership is associated with innovation of higher impact and better quality. Consistent with prior research (He and Tian, 2013), citations are negatively or insignificantly related to firm size and age, negatively related to leverage, and positively related to property, plant, and equipment (PP&E), Tobin's q, and the cash to assets ratio.

3. Hedge Fund Ownership and Patent Generality

Generality captures how broadly a patent impacts future inventions. A higher generality score reflects a patent that receives citations from future patents across a wide range of technology classes, while a lower score indicates that a patent's contribution is concentrated in a small number of technical fields. Models 1–3 in Panel B of Table III analyze patent generality. The dependent variable is patent generality (*GEN*) and the two bias-corrected generality scores (*GEN_tn* and *GEN_tc*) as defined in Appendix B. Our results indicate that *HFH* is positively related to all of the generality measures, and the coefficient estimates are both statistically and economically significant. A 1*SD* increase in *HFH* (10.62%) translates into an increase of 7.5% (*GEN*), 6.7% (*GEN_tn*), and 6.9% (*GEN_tc*) from their respective baseline sample means of 0.04, 0.07, and 0.07 (untabulated). Our results suggest that hedge fund ownership promotes more impactful innovation, whose influence on future inventions is fundamental and broad across many fields of technology.

4. Hedge Fund Ownership and Patent Originality

Originality captures the fundamental nature of a patent relative to its predecessors, with a higher score representing a greater breakthrough rather than marginal innovation. The last three columns in Panel B of Table III provide the regression results of patent originality measures. The dependent variables are *ORG*, *ORG_tn*, and *ORG_tc* as defined in Appendix B. *HFH* is significantly and positively related to *ORG_tn*, but insignificantly related to the other two. A 1*SD* increase in *HFH* (10.62%) amounts to a 4.4% increase in *ORG_tn* from its baseline sample mean of 0.28. Our results provide some evidence that higher hedge fund ownership is associated with more original and radical innovation. Overall, our findings indicate that hedge fund ownership is significantly positively associated not only with patent quantity, but also with important and breakthrough innovation that generates significant impact on future patents.

B. Regressions of Change in Innovation on Change in Hedge Fund Ownership

To further control for endogeneity, we also examine how changes in hedge fund ownership affect future changes in innovation. We estimate multivariate regressions of future changes in innovation proxies from year t to t+1 on changes in *HFH* (Δ*HFH*) from year t-1 to t, changes in control variables, and year and firm fixed effects. Table IV reports the change-on-change regression results.[5] Panel A demonstrates that Δ*HFH* is significantly and positively associated with changes in patent quantity and citations. Panel B reports that Δ*HFH* is also positively

[5] We include changes in all of the control variables used in Equation (1) except for LN_AGE as the effect of its change is captured by the intercept. Our sample size reduces from 33,048 to 25,796 firm-year observations as we take the first differences for the variables used.

Table IV. Regressions of Change in Innovation on Change in Hedge Fund Holdings

This table presents the regression results of change in innovation from year *t* to *t*+1 on the change in hedge fund holdings from year *t*–1 to *t* (ΔHFH), where innovation is measured by patent quantity and citations in Panel A, and patent generality and originality in Panel B. The coefficients on the intercept and the change in control variables from year *t*–1 to *t* (**Δ**LN_MV, **Δ**RD_SALE, **Δ**CAPX_AT, **Δ**PPENT_AT, **Δ**ROA, **Δ**LEV, **Δ**CASH_AT, **Δ**Q, **Δ**HI, and **Δ**HI2) are untabulated for brevity. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. Firm and year fixed effects are included in all of the models. *t*-Statistics (in parentheses) are corrected for firm-level clustering.

Panel A. Patent Quantity and Citations

	ΔLnPAT	ΔLnPAT_tn	ΔLnPAT_tc	ΔLnCite	ΔLnCite_h	ΔLnCite_tn	ΔLnCite_tc
ΔHFH	**0.130****	**0.058***	**0.030***	**0.142*****	**0.245*****	**0.093****	**0.083****
	(2.57)	**(1.85)**	**(1.92)**	**(3.85)**	**(3.16)**	**(2.25)**	**(2.13)**
ΔControl Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.244	0.234	0.279	0.268	0.176	0.097	0.102
N	25,796	25,796	25,796	25,796	25,796	25,796	25,796

Panel B. Patent Generality and Originality

	ΔGEN	ΔGEN_tn	ΔGEN_tc	ΔORG	ΔORG_tn	ΔORG_tc
ΔHFH	**0.031****	**0.059****	**0.064****	**0.037**	**0.215*****	**0.080**
	(2.27)	**(2.11)**	**(2.18)**	**(1.44)**	**(3.20)**	**(1.59)**
ΔControl Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.206	0.181	0.183	0.112	0.096	0.109
N	25,796	25,796	25,796	25,796	25,796	25,796

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

related to changes in generality and originality (except for Δ*Org* and Δ*Org_tc*). Taken together, our change-on-change regressions corroborate the baseline findings, suggesting that hedge fund ownership promotes greater innovative activities and, more importantly, better quality and higher impact innovation.

C. Endogeneity and Instrumental Variable Estimation

Our empirical tests are subject to potential endogeneity concerns. For one, the positive association may be driven by other unobservable factors correlated with both hedge fund ownership and innovation. In addition, hedge funds may choose, ex ante, to invest in firms with greater potential for successful innovation. While using firm fixed effects and change-on-change regressions may help mitigate some of the endogeneity concerns, we attempt to directly control for endogeneity using a 2SLS/IV approach. Specifically, we use two instrumental variables (the S&P 500 inclusion dummy and the state intensity of hedge fund ownership) in order to test the relevance and exclusion criteria in an overidentified system. In the first stage, we regress hedge fund holdings

(*HFH*) on the two instrumental variables chosen. The second stage regresses various measures of innovation on the predicted value of *HFH* from the first stage. We account for all of the control variables and year and firm fixed effects in both stages and estimate them jointly.

Following Aghion et al. (2013), we consider the inclusion of a firm in the S&P 500 index as the first instrument. Specifically, *S&P 500* is a dummy variable that is equal to one if the firm is included in the S&P 500 index in year *t* and zero otherwise. Prior literature suggests that hedge funds tend to invest in smaller firms, partly due to the easiness and flexibility of accumulating a significant ownership stake in target firms with a given amount of capital (Brav, Jiang, and Kim, 2012). Therefore, hedge funds are less prone to broad indexing. Furthermore, Gantchev and Jotikasthira (2013) find that hedge funds (in particular hedge fund activists) tend to trade against other institutions when the latter exit their equity position in a firm. Thus, we expect a negative relation between the S&P 500 inclusion dummy and hedge fund ownership (the relevance criterion). This instrument is likely to satisfy the exclusion criterion. A firm is added to the S&P 500 index because it represents its industry or sector well, not due to the firm's expected performance or innovation potential. Indeed, Standard and Poor's explicitly states that the criteria for being added to the index are not based on a firm's investment potential (Aghion et al. 2013).[6]

Our second instrument is the state-level intensity of hedge fund ownership (*HFHState*), defined as the proportion of total market capitalization of all public firms headquartered in a state in year *t* that are held by our sample hedge funds. This instrument is motivated by previous studies, which find that firms located in the same geographical area tend to share a common investor base (Coval and Moskowitz, 2001; Grinblatt and Keloharju, 2001; Pirinsky and Wang, 2006; Brown, Ivković, Smith, and Weisbenner, 2008). Thus, we expect that firms headquartered in a state with a higher level of *HFHState* are more likely to be held by hedge funds (the relevance criterion). However, it seems unlikely that this state intensity will directly affect an individual firm's innovative activities other than through its impact on hedge fund holdings in a firm (the exclusion criterion). We conduct statistical tests to ensure that the two instruments jointly meet the relevance and exclusion criteria.[7]

Table V reports the 2SLS/IV regression results. The first stage regression shows that *S&P 500* (*HFHState*) is significant and negative (positive) in predicting *HFH* with a *t*-statistic of –5.49 (3.74). The first stage *F*-test reports that the weak instruments problem is of little concern and the two instrumental variables are relevant (*F*-statistic = 12.61). After controlling for endogeneity, the second stage results indicate that *HFH* remains significant and positive in predicting patent quantity, citations, and generality.[8] A 1*SD* increase in *HFH* (10.62%) results in an increase of 0.45 (*LnPAT*), 0.18 (*LnPAT_tn*), 0.38 (*LnCite*), 0.16 (*LnCite_tn*), 0.06 (*GEN*), and 0.12 (*GEN_tn*), respectively. Given a baseline sample mean (untabulated) of 0.50, 0.28, 0.17, 0.14, 0.04, and 0.07 for the respective innovation variables, the increases are both statistically and economically

[6] S&P Indices General Disclaimer states: "Inclusion of a security within an index is not a recommendation by S&P Dow Jones Indices to buy, sell, or hold such security, nor is it considered to be investment advice." (http://www.standardandpoors.com/ regulatory-affairs/indices/en/us).

[7] One concern is that if hedge funds choose to locate in states with more innovative firms due to lower monitoring or information acquisition costs and invest more in local firms, then firms headquartered in these states might exhibit higher levels of *HFHState*. These firms are also more innovative, inducing a correlation between *HFHState* and innovation. We thank the referee for this insight. Following Field, Lowry, and Mkrtchyan (2013), we conjecture that the rapid advancement of technology and communications at least partially alleviates this concern, as hedge funds may have more freedom regarding geographic location.

[8] For brevity, we only present results for innovation measures without industry and time adjustments, and those adjusted for USPTO technology class and application year. Untabulated tests produce qualitatively similar results if we use the HJT category adjustment or the quasi-structural method.

Table V. Two-Stage Least-Squares/Instrumental Variable Regressions

This table presents the two-stage least squares/instrumental variable (2SLS/IV) regression results. The first stage regresses hedge fund holdings (HFH) on the two instrumental variables, the S&P 500 inclusion dummy (S&P 500) and the state intensity of hedge fund ownership (HFHState). The second stage regresses various innovation measures on the fitted value of HFH from the first stage. All of the control variables (LN_MV, RD_SALE, CAPX_AT, PPENT_AT, ROA, LEV, CASH_AT, Q, HI, HI2, and LN_AGE) are included in both stages, but untabulated for brevity. The two stages are estimated jointly. The first-stage *F*-test statistic for instrument validity and the *p*-values for Hansen *J*-statistics of overidentification tests for the second stage are reported. Firm and year fixed effects are included in all of the regressions. Intercepts and control variables are omitted for brevity. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. *t*-Statistics (in parentheses) are corrected for firm-level clustering.

	1st Stage	2nd Stage							
	HFH	LnPAT	LnPAT_tn	LnCite	LnCite_tn	GEN	GEN_tn	ORG	ORG_tn
HFH		**4.204***** **(3.10)**	**1.660**** **(2.16)**	**3.543***** **(3.65)**	**1.464**** **(2.07)**	**0.603**** **(2.17)**	**1.129**** **(2.09)**	**−0.445** **(−1.02)**	**0.062** **(0.06)**
S&P 500	−0.024*** (−5.49)								
HFHState	0.098*** (3.74)								
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.727	0.729	0.775	0.443	0.455	0.386	0.386	0.579	0.513
N	30,875	30,875	30,875	30,875	30,875	30,875	30,875	30,875	30,875
1st stage test statistic									
F-statistic for IV	12.61								
2nd stage over-identification test									
p-Value for Hansen *J*-statistic		0.9997	0.9999	0.4446	0.8276	0.9254	0.9667	0.2745	0.9327

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

significant. The results also indicate that ordinary least square (OLS) regressions underestimate the effect of *HFH* on innovation. Finally, the Hansen *J*-tests for overidentification in the second stage demonstrate that the two instruments are jointly exogenous and valid (e.g., the *p*-values for Hansen *J*-statistics range from 0.2754 to 0.9999).

Overall our main results are robust after controlling for endogeneity using 2SLS/IV estimation, indicating that higher hedge fund ownership leads to greater innovative activities and higher quality innovation.

D. Dynamic Panel GMM Estimation

To further address the endogeneity problem, we follow Wintoki et al. (2012) and apply a dynamic panel GMMs estimator in this section.[9] Specifically, we estimate the following dynamic GMM model using the method of Blundell and Bond (1998):

$$Innovation_{i,t+1} = \alpha_t + \gamma_i + \rho \text{Innovation}_{i,t} + \beta HFH_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}, \tag{2}$$

where *Innovation* is a measure of patent quantity, citations, generality, or originality, *HFH* denotes hedge fund ownership, X contains all of the control variables, and α_t and γ_i are year and firm fixed effects, respectively. Table VI provides the dynamic panel GMM estimation results, where innovation is measured by patent quantity and citations in Panel A, and generality and originality in Panel B.[10] The coefficients on *HFH* are significantly positive for all measures of patent quantity and originality, as well as the two measures of patent citations (*LnCite_tn* and *LnCite_tc*). In general, we document qualitatively similar results after controlling for endogeneity using dynamic panel GMM estimators.

E. Firms with Missing Hedge Fund Ownership

We use a sample of firms with nonmissing hedge fund ownership. A natural question might be do uncovered firms generate more innovative activities than covered firms? To address this question, we expand our sample to include Compustat firms with missing hedge fund ownership. The expanded sample has 44,262 firm-year observations, of which 33,048 have nonmissing *HFH* and the remaining 11,214 are not covered by our hedge fund data set. We create a dummy variable (*HFH_Dummy*) that is equal to one if a firm has nonmissing *HFH* in year *t*, and zero otherwise. In untabulated analysis, *HFH_Dummy* is significant and positive suggesting that covered firms are associated with significantly greater innovation quantity, quality, generality, and originality than uncovered firms. Therefore, the positive correlation between hedge fund ownership and innovation is robust and not driven by our focus on a sample of firms covered in the hedge fund data set.

F. Hedge Fund Blockholdings

To provide further insight into the effect of hedge fund ownership on innovation, we examine hedge fund blockholdings from two perspectives. First, we examine whether the relationship between hedge fund ownership and corporate innovation is more evident when hedge funds as a

[9] For studies using dynamic panel GMM estimation, see also Roodman (2009), Warr et al. (2012), and Flannery and Hankins (2013), among others.

[10] For brevity, we do not report the coefficients on the lagged innovation variables, control variables, and year dummies. For details on the dynamic panel GMM estimation and the Stata program used, see the appendix of Wintoki et al. (2012).

Table VI. Dynamic Panel GMM Estimation

This table estimates the following dynamic GMM model using the method of Blundell and Bond (1998):

$$Innovation_{i,t+1} = \alpha_t + \gamma_i + \rho Innovation_{i,t} + \beta HFH_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},$$

where *Innovation* is measured by patent quantity and citations in Panel A, and patent generality and originality in Panel B, *HFH* denotes hedge fund ownership, *X* contains all of the control variables (LN_MV, RD_SALE, CAPX_AT, PPENT_AT, ROA, LEV, CASH_AT, Q, HI, HI2, and LN_AGE), and α_t and γ_i are year and firm fixed effects, respectively. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. For brevity, only the coefficients on *HFH* are reported. *t*-Statistics (in parentheses) are corrected for firm-level clustering.

Panel A. Patent Quantity and Citations

	LnPAT	LnPAT_tn	LnPAT_tc	LnCite	LnCite_h	LnCite_tn	LnCite_tc
HFH	**0.545****	**0.358*****	**0.168*****	**0.0417**	**0.695**	**0.484****	**0.428****
	(2.30)	**(3.06)**	**(2.88)**	**(0.41)**	**(1.41)**	**(2.20)**	**(2.04)**
N	25,548	25,548	25,548	25,548	25,548	25,548	25,548

Panel B. Patent Generality and Originality

	GEN	GEN_tn	GEN_tc	ORG	ORG_tn	ORG_tc
HFH	**0.099**	**0.208**	**0.233**	**0.354****	**0.730****	**0.703*****
	(1.37)	**(1.38)**	**(1.46)**	**(2.55)**	**(2.52)**	**(2.67)**
N	25,548	25,548	25,548	25,548	25,548	25,548

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

whole have a significant stake in a firm. Edmans (2009) finds that blockholders' ability to sell large stakes causes stock prices to reflect a firm's fundamental value, which, in turn, encourages managers to innovate. Blockholders may also have stronger incentives to monitor managers due to their large stakes in the firm (Aghion et al., 2013). We expect that hedge funds should collectively have a reasonable size of ownership in a firm in order to affect innovation. In addition, hedge funds may not have incentives to influence managerial decisions if their investment in the firm is not large enough to make a difference in their investment returns. Therefore, hedge fund ownership that constitutes a more significant fraction of a fund's assets under management should have a greater impact on innovation.

To address the first issue, we add an interaction term to Equation (1), *HFH∗Block*, where *Block* is equal to one if *HFH* in a firm is above the median *HFH* of the full sample, and zero otherwise. In Panel A of Table VII, we only present coefficient estimates for our variables of interest to save space. We find that the coefficients on the interaction term (*HFH∗Block*) are generally significant and positive across all of the models, suggesting the relation between innovation and *HFH* is significantly greater for the above-median levels of *HFH* (i.e., hedge fund blockholdings) than for the below-median levels. Indeed, the coefficients on *HFH*, indicative of the effect of the below-median levels of *HFH*, are generally negative. These findings are consistent with our

Table VII. Hedge Fund Blockholdings

Panel A reports coefficients on hedge fund holdings (HFH) and the interactive terms between HFH and Block (HFH∗Block) from the regressions:

$$Innovation_{i,t+1} = \alpha_t + \gamma_i + \beta_1 HFH_{i,t} + \beta_2 HFH_{i,t} * Block_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},$$

Where *Innovation* is a measure of patent quantity, citations, generality, or originality; *Block* is an indicator variable that is equal to one if *HFH* in a firm is above the median *HFH* of the full sample, and zero otherwise; *X* contains all of the control variables (LN_MV, RD_SALE, CAPX_AT, PPENT_AT, ROA, LEV, CASH_AT, Q, HI, HI2, and LN_AGE), and α_t and γ_i are year and firm fixed effects, respectively. Panel B reports coefficients on HFH from the regressions for the two groups (HI and LO):

$$Innovation_{i,t+1} = \alpha_t + \gamma_i + \beta_1 HFH_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}$$

If a hedge fund's ownership in a firm is above (below) 5% of the fund's assets under management, it is assigned to a HI (LO) group. *HFH* for the HI (LO) group is measured as the sum of shares held by hedge funds in the HI (LO) group divided by the total number of shares outstanding for the firm. The coefficient differences on HFH between HI and LO groups with the *p*-values for *z*-statistics are provided in Panel B. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. *t*-Statistics (in parentheses) are corrected for firm-level clustering.

Panel A. Hedge Fund Blockholdings

	LnPAT	LnPAT_tn	LnPAT_tc	LnCite	LnCite_h	LnCite_tn	LnCite_tc	GEN	GEN_tn	GEN_tc	ORG	ORG_tn	ORG_tc
HFH	−0.449*	−0.449***	−0.306***	−0.278*	−0.334	−0.243*	−0.253*	−0.106**	−0.231**	−0.227**	−0.166*	−0.235	−0.349**
	(−1.88)	(−3.04)	(−3.58)	(−1.68)	(−1.10)	(−1.77)	(−1.93)	(−2.00)	(−2.23)	(−2.09)	(−1.92)	(−1.09)	(−2.08)
HFH∗Block	**0.642****	**0.592*****	**0.407*****	**0.374****	**0.510***	**0.268****	**0.282****	**0.124****	**0.261*****	**0.261*****	**0.157***	**0.331***	**0.325****
	(2.50)	**(3.71)**	**(4.42)**	**(2.44)**	**(1.80)**	**(2.11)**	**(2.33)**	**(2.53)**	**(2.72)**	**(2.58)**	**(1.95)**	**(1.65)**	**(2.09)**
R^2	0.815	0.834	0.857	0.546	0.574	0.497	0.511	0.429	0.426	0.423	0.611	0.535	0.608
N	33,048	33,048	33,048	33,048	33,048	33,048	33,048	33,048	33,048	33,048	33,048	33,048	33,048

Panel B. HFH Above 5% of AUM (HI) vs. Below 5% (LO)

		LnPAT	LnPAT_tn	LnPAT_tc	LnCite	LnCite_h	LnCite_tn	LnCite_tc	GEN	GEN_tn	GEN_tc	ORG	ORG_tn	ORG_tc
HI	HFH	0.699*	0.413	0.295*	0.337**	0.679**	0.203	0.223	0.064	0.127	0.138	−0.030	0.350	−0.068
(> = 5%)	*t*-Stat.	(1.72)	(1.55)	(1.67)	(2.27)	(2.15)	(1.33)	(1.49)	(1.54)	(1.59)	(1.55)	(−0.30)	(1.30)	(−0.34)
(*N* = 3,650)	R^2	0.877	0.887	0.893	0.713	0.740	0.682	0.689	0.645	0.645	0.634	0.734	0.658	0.729
LO	HFH	0.110*	0.084**	0.066***	0.005	0.034	0.002	0.001	0.001	−0.003	−0.000	0.006	0.123**	0.012
(<5%)	*t*-Stat.	(1.87)	(2.33)	(3.25)	(0.14)	(0.51)	(0.06)	(0.05)	(0.11)	(−0.13)	(−0.00)	(0.33)	(2.53)	(0.31)
(*N* = 29,497)	R^2	0.790	0.810	0.835	0.509	0.549	0.476	0.496	0.384	0.386	0.382	0.590	0.511	0.587
HI – LO	**Diff.**	**0.590***	**0.337**	**0.234***	**0.332****	**0.654****	**0.209***	**0.230***	**0.065***	**0.146***	**0.144***	**−0.035**	**0.229**	**−0.079**
	p-Value	0.075	0.105	0.095	0.016	0.022	0.093	0.069	0.071	0.051	0.066	0.635	0.205	0.653

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

hypothesis that hedge funds should collectively have significant ownership stakes in a firm in order to affect innovation.[11]

To address the second issue, for each firm in each year, we assign hedge funds with holdings in the firm into two groups depending upon whether their holdings constitute at least 5% of their total assets under management (AUM). Specifically, if a hedge fund's ownership in a firm is above (below) 5% of the fund's AUM, it is assigned to a HI (LO) group. We then construct *HFH* for the HI (LO) group as the sum of shares held by the hedge funds in the HI (LO) group divided by the total number of shares outstanding for the firm. Next, we rerun Equation (1) and present the coefficient estimates on *HFH* for both groups. Finally, we conduct *z*-tests for the differences in coefficients of *HFH* across the HI and LO groups. Panel B of Table VII finds that while the coefficients on *HFH* are positive for both groups in general, they are significantly larger in HI than in LO, suggesting that hedge funds are more likely to foster innovation if their holdings in the firm represent a significant share of their assets under management.

III. The Mechanism: R&D Input and Innovation Efficiency

We now explore the mechanism through which hedge fund ownership affects innovation. First, hedge funds may affect the total amount of innovative input, R&D, to increase innovation output. Additionally, hedge funds may enhance innovation output by improving the productivity of R&D and innovation efficiency without necessarily affecting R&D input. The two channels are not mutually exclusive and can be in force simultaneously. Sections IIIA and IIIB examine R&D input and innovation efficiency, respectively. Section IIIC studies cross-sectional differences as the mechanism may function differently depending upon the environment in which a firm operates.

A. Innovative Input: R&D Intensity

Given the positive correlations between innovation output and R&D input as shown in Table II, it is natural to examine first and foremost whether hedge funds affect innovation output by influencing input. Panel A of Table VIII reports the OLS (level and change) and 2SLS/IV regressions of R&D intensity, defined as the R&D to assets (*RD_AT*) and R&D to sales (*RD_Sale*) ratios. Neither *HFH* nor Δ*HFH* is significantly associated with future R&D intensity suggesting that hedge funds do not increase R&D input in order to boost innovation output. In fact, the OLS regression indicates that *HFH* is negatively related to *RD_AT*, albeit marginally. This is somewhat consistent with hedge fund activists targeting lower R&D firms (Brav et al., 2008).[12] Next, we explore whether hedge funds may influence innovation output by enhancing R&D productivity.

[11] We also decompose the full sample into five quintiles each year with Q5 (Q1) having the largest (smallest) *HFH*, and re-estimate Equation (1) for each quintile. Untabulated results indicate that the coefficients on *HFH* for Q5 are, in general, significantly larger than those for Q1, corroborating our findings in Panel A of Table VII.

[12] This is not necessarily in conflict with our main findings that hedge funds increase innovation output. Indeed, hedge funds may target low R&D firms and then increase R&D to the extent that valuable growth opportunities (e.g., productive R&D and efficient innovation) are available. This conjecture is supported by the evidence in the cross section (Section IIIC). Hedge funds appear to increase *future* spending in (productive) R&D, alter the composition of R&D, and enhance innovation efficiency in targeted firms with ex ante lower R&D, thereby improving innovation output and creating higher investment returns for the funds.

Table VIII. The Mechanism: R&D Input and Innovation Efficiency

This table examines the mechanism through which hedge fund ownership affects innovation. Panels A and B present OLS (level-on-level and change-on-change) and the second stage estimation of two-stage least squares/instrumental variable (2SLS/IV) regressions of R&D intensity and innovation efficiency, respectively, on hedge fund holdings (HFH). For level regressions, the dependent (independent) variables are levels measured at the end of year $t+1$ (year t) and control variables include LN_MV, RD_SALE, CAPX_AT, PPENT_AT, ROA, LEV, CASH_AT, Q, HI, HI2, and LN_AGE. For change regressions, the dependent (independent) variables are changes from year t to $t+1$ (from year t–1 to t). Control variables exclude LN_AGE as the effect of its change is captured by the intercept. The first-stage F-test statistic for instrument validity and the p-values for Hansen J-statistics of overidentification tests for the second stage are reported for 2SLS/IV regressions. Firm and year fixed effects are included in all of the regressions. t-Statistics (in parentheses) are corrected for firm-level clustering. Intercepts and control variables are omitted for brevity. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels.

Panel A. R&D Intensity

	RD_AT_{t+1}			RD_Sale_{t+1}		
Dep. Var.	**Level**	**Change**	**2SLS/IV**	**Level**	**Change**	**2SLS/IV**
HFH	**−0.014***		**−0.162**	**−0.243**		**3.455**
	(−1.77)		**(−0.86)**	**(−0.59)**		**(0.35)**
ΔHFH		**−0.015**			**−0.354**	
		(−1.51)			**(−0.79)**	
Control Variables	Level	Change	Level	Level	Change	Level
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.753	0.263	0.749	0.533	0.162	0.532
N	33,048	25,796	30,875	33,048	25,796	30,875
1st Stage F-stat.			12.61			12.61
Hansen J-stat. p-value			0.1821			0.9472

Panel B. Innovation Efficiency

	$Ln\left(\frac{1+PAT_{t+1}}{1+R\&D_t}\right)$			$Ln\left(\frac{1+AllCites_{t+1}}{1+R\&D_t}\right)$		
Dep. Var.	**Level**	**Change**	**2SLS/IV**	**Level**	**Change**	**2SLS/IV**
HFH	**0.104***		**9.431*****	**0.335*****		**15.487*****
	(1.64)		**(4.61)**	**(3.89)**		**(5.13)**
ΔHFH		**0.100***			**0.180****	
		(1.67)			**(2.53)**	
Control variables	Level	Change	Level	Level	Change	Level
Firm and year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.836	0.268	0.731	0.775	0.319	0.591
N	33,048	25,796	30,875	33,048	25,796	30,875
1st Stage F-stat.			12.61			12.61
Hansen J-stat. p-value			0.2149			0.2677

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

B. R&D Productivity and Innovation Efficiency

Prior literature suggests that hedge fund ownership may increase innovation output by enhancing innovation efficiency without necessarily enlarging R&D input. Almeida et al. (2013) find that financial constraints can improve innovation efficiency by mitigating agency problems of free cash flow that induce managers to make unproductive R&D investment in fields out of their direct expertise. Since R&D projects constitute both marginal and radical innovations, hedge funds may alter the mix of the R&D program and motivate resource allocation toward innovative, productive, high quality projects, and projects within the managers' direct area of expertise, while curtailing unproductive and marginal ones.[13] In addition, Gonzalez-Uribe (2013) finds that venture capital facilitates the diffusion of knowledge among firms in their portfolios thus improving patent citations of these firms. We conjecture that hedge funds may learn from the patenting experience and innovation expertise of firms in their investment portfolios and facilitate knowledge diffusion among them, thereby enhancing the innovation output of these firms. Further, if there are some fixed costs in setting up effective monitoring across firms, then hedge funds, which typically hold large blocks in several firms, can exploit economies of scale and monitor these firms more effectively. Finally, Aghion et al. (2013) confirm that institutional investors have only a small positive effect on R&D, but a large positive effect on patents, suggesting that the main effect of ownership is to alter the quality and/or productivity of R&D rather than stimulate more R&D input.[14] Following Li (2011), Hirshleifer, Hsu, and Li (2013), and Almeida et al. (2013), we construct two sets of innovation efficiency measures. $\ln\left(\frac{1+PAT_{t+1}}{1+R\&D_t}\right)$ is defined as the natural logarithm of the ratio of one plus the total number of patents filed in application year $t+1$ to one plus R&D expenses (in \$000's) in the previous year t. $\ln\left(\frac{1+AllCites_{t+1}}{1+R\&D_t}\right)$ is the natural logarithm of the ratio of one plus the total number of citations received in life on all of the patents filed in application year $t+1$ to one plus R&D expenses (in \$000's) in year t.[15] All of the results hold if we use bias-adjusted measures. As demonstrated in Panel B of Table VIII, *HFH* is significant and positive in explaining both measures of innovation efficiency, across all models, suggesting that *HFH* enhances innovation efficiency and R&D productivity.

C. Cross-Sectional Heterogeneity

To further shed light on the channels through which hedge fund holdings affect innovation, we examine the cross-sectional heterogeneity in the effect of *HFH*. Specifically, we re-estimate Equation (1) by adding an interaction term between *HFH* and a dummy variable indicating firms with a high value of the partitioning variable (i.e., above median value) in year t and report the

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[13] The ultimate success of innovative R&D also depends upon the types of people heading the R&D organization and recruited to engage in R&D projects. We conjecture that hedge funds can influence firms to adopt policies promoting efficient R&D, which also dictates the recruitment of appropriate personnel in accordance with the goals of these policies.

[14] The intuition is, at any moment in time in innovative firms, there are many unpatented ideas as patenting them requires effort, time, and money. The very first move to stimulate innovation is to patent these ideas leading to an increase in new patents.

[15] These efficiency measures enable us to include observations with zero R&D. For robustness, we also use patent quantity and citations scaled by R&D expenses, reducing our sample to 17,372 firm-year observations. Untabulated analyses find that the positive relation between innovation efficiency and *HFH* still holds for OLS level and change regressions, but becomes insignificant in the 2SLS/IV regressions. This is likely due to the exclusion of zero R&D firms and highlights the importance of treating zero R&D firms appropriately.

results in Table IX. Again, for brevity, we only tabulate the coefficient estimates on *HFH* and the interactive term.[16]

1. Importance of Innovation Output

If hedge funds foster innovation by enhancing R&D productivity, we expect this effect to be stronger in more innovative firms, where innovation output and efficiency are crucial for their long-term success. In Panel A of Table IX, our variable of interest is the interactive term between *HFH* and *LnPAT_H* (*HFH*∗*LnPAT_H*), where *LnPAT_H* is equal to one (zero) if the firm has above (below) median *LnPAT*. This interaction term is significant and positive in predicting innovation output, innovation efficiency, and even R&D intensity suggesting that the positive effect of *HFH* on innovation is greater in more innovative firms. Interestingly, *HFH* increases R&D in firms with greater innovation output, but decreases R&D in firms with less successful output corroborating our finding that hedge funds foster successful innovation by increasing efficiency rather than input, thus promoting more efficient resource allocation of the R&D program. We find consistent evidence in Panel B when *LnCite_H* is used to capture innovation importance, which is defined as one (zero) if the firm's *LnCite* is above (below) the sample median.

2. R&D Expenditures

In Panel C of Table IX, we examine the effect of *HFH* on innovation, conditioned upon R&D input (i.e., RD_AT).[17] The positive relationship between innovation and *HFH* appears to be stronger for firms with ex ante below median R&D, consistent with hedge fund activists targeting low R&D firms (Brav et al., 2008). Our findings further suggest that hedge funds can motivate low R&D firms to increase both R&D input and productivity, generating more successful innovation, greater firm value, and higher returns for hedge funds.[18]

3. Free Cash Flow, Leverage, and Financial Constraints

We also condition our analysis on free cash flow and financial leverage as firms with more resources and less financial constraints may be able to provide more consistent R&D funding through time. As such, improving innovation efficiency may not be the main goal. In contrast, firms with lower cash flow or a higher leverage ratio are more susceptible to financial constraints and distress risk, but less likely to suffer from agency problems of free cash flow (Jensen, 1986) or overinvestment in inferior R&D. For these firms, increasing efficiency rather than input is more crucial and relevant (Almeida et al., 2013). Thus, we expect the positive effect of *HFH* on innovation output and efficiency to be stronger in low cash and high leverage firms. We find consistent evidence in Panels D and E.

4. Market Valuation

Aghion et al. (2013) find that institutional investors can encourage innovation if they reduce managerial career concerns via effective monitoring. Given that managers in firms with lower market valuation are subject to greater career concerns due to increased takeover threat and

[16] We only report results for unadjusted patent measures (*LnPAT*, *LnCite*, *GEN*, and *ORG*) to save space, but all of the results continue to hold for bias-adjusted patent measures.

[17] The results are qualitatively similar if we use *RD_Sales* or *Ln(1+RD)*.

[18] To the extent that low R&D proxies for financial constraints, our evidence also suggests that hedge funds may increase innovation efficiency for financially constrained firms who value efficiency (rather than input) the most.

Table IX. The Mechanism: Exploring Cross-Sectional Heterogeneity

The table reports coefficient estimates on hedge fund holdings (HFH) and the interactive term between HFH and a dummy variable indicating firms with a high partitioning variable in year t (HFH∗D) from the following regression:

$$Innovation_{i,t+1} = \alpha_t + \gamma_i + \beta_1 HFH_{i,t} + \beta_2 HFH_{i,t} * D_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},$$

where D refers to LnPat_H, LnCite_H, RD_H, Cash_H, Lev_H, Q_H, or Compete_L, *Innovation* is a measure of patent, patent efficiency, or R&D, X contains all of the control variables (LN_MV, RD_SALE, CAPX_AT, PPENT_AT, ROA, LEV, CASH_AT, Q, HI, HI2, and LN_AGE), and α_t and γ_i are year and firm fixed effects, respectively. LnPAT_H is equal to one (zero) if a firm has LnPAT above (below) the sample median. LnCite_H is equal to one (zero) if a firm has LnCite above (below) the median. RD_H is equal to one (zero) if a firm has RD_AT above (below) the median. Cash_H is equal to one (zero) if a firm has CASH_AT above (below) the median. Lev_H is equal to one (zero) if a firm has LEV above (below) the median. Q_H is equal to one (zero) if a firm has Q above (below) the median. Compete_L is equal to one (zero) if a firm has a less (more) competitive product market with the industry HI above (below) the median. All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. t-Statistics (in parentheses) are corrected for firm-level clustering.

	LnPAT	LnCite	GEN	ORG	$Ln\left(\frac{1+PAT_{t+1}}{1+R\&D_t}\right)$	$Ln\left(\frac{1+AllCites_{t+1}}{1+R\&D_t}\right)$	RD_AT
Panel A. High Innovation Quantity: LnPAT_H							
HFH	−0.515***	0.006	0.004	−0.571***	−0.601***	0.190**	−0.019**
	(−9.85)	(0.16)	(0.31)	(−13.30)	(−9.36)	(2.14)	(−2.31)
HFH∗LnPAT_H	**3.928*** **	**0.638*** **	**0.123*** **	**3.940*** **	**4.052*** **	**0.833*** **	**0.027** **
	(53.15)	**(12.78)**	**(7.66)**	**(64.98)**	**(44.64)**	**(6.63)**	**(2.42)**
Panel B. High Innovation Quality: LnCite_H							
HFH	−0.431***	−0.175***	−0.030***	−0.134***	−0.534***	−0.412***	−0.015*
	(−8.54)	(−5.23)	(−2.71)	(−7.58)	(−8.60)	(−4.91)	(−1.93)
HFH∗LnCite_H	**5.469*** **	**2.668*** **	**0.502*** **	**1.222*** **	**5.827*** **	**6.831*** **	**0.014**
	(64.65)	**(47.41)**	**(27.06)**	**(41.08)**	**(55.90)**	**(48.45)**	**(1.04)**
Panel C. High R&D Intensity: RD_H							
HFH	1.080***	0.823***	0.194***	0.225***	1.889***	2.714***	0.026***
	(16.37)	(19.46)	(14.21)	(10.08)	(24.06)	(25.90)	(2.70)
HFH∗RD_H	**−1.976*** **	**−1.529*** **	**−0.366*** **	**−0.489*** **	**−3.866*** **	**−5.151*** **	**−0.086*** **
	(−23.12)	**(−27.93)**	**(−20.71)**	**(−16.90)**	**(−38.01)**	**(−37.96)**	**(−6.89)**
Panel D. High Cash: Cash_H							
HFH	0.479***	0.342***	0.078***	0.090***	0.594***	0.975***	0.013
	(7.54)	(8.36)	(5.92)	(4.20)	(7.73)	(9.51)	(1.38)
HFH∗Cash_H	**−0.607*** **	**−0.438*** **	**−0.103*** **	**−0.176*** **	**−0.955*** **	**−1.246*** **	**−0.052*** **
	(−9.02)	**(−10.13)**	**(−7.40)**	**(−7.79)**	**(−11.74)**	**(−11.48)**	**(−5.27)**
Panel E. High Leverage Ratio: Lev_H							
HFH	0.027	−0.031	−0.012	−0.056**	−0.086	0.065	−0.040***
	(0.42)	(−0.74)	(−0.88)	(−2.56)	(−1.10)	(0.62)	(−4.21)
HFH∗Lev_H	**0.264*** **	**0.277*** **	**0.069*** **	**0.104*** **	**0.357*** **	**0.509*** **	**0.049*** **
	(3.85)	**(6.27)**	**(4.87)**	**(4.48)**	**(4.30)**	**(4.59)**	**(4.87)**

(Continued)

Table IX. The Mechanism: Exploring Cross-Sectional Heterogeneity *(Continued)*

	LnPAT	LnCite	GEN	ORG	$Ln\left(\frac{1+PAT_{t+1}}{1+R\&D_t}\right)$	$Ln\left(\frac{1+AllCites_{t+1}}{1+R\&D_t}\right)$	RD_AT
Panel F. High Market Valuation: Q_H							
HFH	0.216***	0.194***	0.038***	0.047**	0.203***	0.481***	0.010
	(5.61)	(4.87)	(2.98)	(2.26)	(2.70)	(4.80)	(1.06)
HFH∗Q_H	**−0.195*** **	**−0.155*** **	**−0.026** **	**−0.096*** **	**−0.198*** **	**−0.290*** **	**−0.046*** **
	(−5.00)	**(−3.83)**	**(−2.03)**	**(−4.51)**	**(−2.60)**	**(−2.85)**	**(−5.07)**
Panel G. Low Product Market Competition (High Industry HI): Compete_L							
HFH	0.175***	0.174***	0.046***	0.006	0.124	0.379***	−0.026***
	(2.70)	(4.16)	(3.39)	(0.27)	(1.57)	(3.61)	(−2.74)
HFH∗Compete_L	**−0.015**	**−0.115** **	**−0.041*** **	**−0.013**	**−0.040**	**−0.088**	**0.024** **
	(−0.21)	**(−2.40)**	**(−2.69)**	**(−0.53)**	**(−0.45)**	**(−0.74)**	**(2.26)**

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

dismissal risk (Stein, 1988), we expect the positive effect of hedge fund ownership on innovation to be stronger for these firms. Panel F reports a negative coefficient on the interaction term between *HFH* and *Q_H*, where *Q_H* is equal to one if the firm's Tobin's q is above the median and zero otherwise. This evidence suggests that hedge funds improve innovation in low q firms, where managerial career concerns and myopia are most severe.

5. Product Market Competition

Brav et al. (2013) find that a typical target firm of hedge fund activists improves its production efficiency within three years after the intervention, and this improvement is pronounced only in competitive industries. Analogously, we anticipate that the positive association between hedge fund ownership and innovation should be more pronounced in competitive rather than noncompetitive industries. Panel G illustrates that this positive association is indeed stronger in competitive industries (i.e., low industry Herfindahl index). Moreover, the negative relation between *HFH* and R&D is more pronounced in competitive industries than noncompetitive ones. These results suggest that consistent with the prior literature (Brav et al., 2008; Aghion et al., 2013), hedge funds appear to increase innovation efficiency and decrease unproductive R&D only in competitive industries, where productivity and efficiency are more important for firm survival and long-term growth.

IV. Innovation, Hedge Fund Ownership, and Firm Value

Innovation enhances a firm's competitiveness and ultimately creates long-term firm value. Hedge funds care about innovation not because they care about the social returns innovation may bring, but because innovation can generate higher returns for their investment. In fact, a positive correlation between innovation and firm value is well documented in the literature. For example, Hall, Jaffe, and Trajtenberg (2005), Pakes (1985), Griliches (1990), Lerner (1994), Deng, Lev, and Narin (1999), Lanjouw and Schankerman (2004), Gu (2005), Matolcsy and Wyatt (2008), and Pandit, Wasley, and Zach (2011) find a positive relation between patent counts or patent citations and firms' returns, operating performance, and market value. Thus, hedge funds may increase firm value by promoting innovation quantity and quality. In return, increases in firm value are translated into higher investment returns for hedge funds. We now examine the impact of hedge fund ownership on firm value (via its effect on innovation) by estimating the equation as follows:

$$\begin{aligned} \mathit{FirmValue}_{i,t+1} = {} & \alpha_t + \gamma_i + \beta_1 \mathit{HFH}_{i,t} + \beta_2 \mathit{Innovation}_{i,t+1} \\ & + \beta_3 \mathit{Innovation}_{i,t+1} * \mathit{HFH}_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1}, \end{aligned} \tag{3}$$

where firm value is approximated by Tobin's q measured at the fiscal end of year $t+1$, *HFH* is hedge fund holdings, *Innovation* is one of the innovation measures, X contains all of the control variables, and α_t and γ_i are year and firm fixed effects, respectively.

We estimate Equation (3) using both OLS and 2SLS/IV regressions. Our variable of interest is the interaction term between the innovation measures and hedge fund ownership (i.e., $\mathit{Innovation} * \mathit{HFH}$). A positive β_3 is consistent with hedge fund ownership increasing firm value through its positive effect on innovation, while a negative β_3 suggests otherwise.

A. OLS Regressions

Panel A of Table X reports the OLS regression results of Equation (3). Consistent with the extant literature, all of the patent measures are significantly positively related to firm value. The coefficients on *HFH* are also significant and positive, suggesting a positive effect on firm value. More importantly, the coefficient estimates on the interaction terms between patent quantity and *HFH* are all significant and positive. It appears that an increase in patents generated in firms with larger hedge fund holdings is associated with higher firm value. Likewise, the interactive terms between most patent citations and originality measures and *HFH* are also significantly positive suggesting that hedge funds enhance firm value by increasing both innovation quantity and quality. The coefficient estimates on the control variables (untabulated for brevity) are in line with prior studies. For example, Q_{t+1} is positively related to R&D intensity, PP&E, and the cash to assets ratio, but negatively related to market capitalization, capital expenditures, ROA, and firm age.

B. 2SLS/IV Regressions

It is possible that both hedge fund ownership and patent innovation are endogenous. To address this concern, we adopt the 2SLS/IV approach and instrument both variables. *HFH* is instrumented in the first stage by the S&P 500 inclusion dummy (*S&P 500*) and hedge fund ownership state density (*HFHState*) as defined in Section IIC. Patent measures are instrumented by *Silicon Valley*, which is equal to one if the firm's headquarters are located within 100 kilometers of the center of Silicon Valley and zero otherwise.[19] This instrument is motivated by the conjecture that innovative firms are more likely to be located in Silicon Valley, thereby minimizing the costs of raising capital and information acquisition due to the close geographical proximity to

[19] Another possible instrument for patent measures is the existence of state antitakeover legislation (*BC*), defined as an indicator variable equal to one if the headquartered state of a firm has passed Business Combination laws as of year t, and zero otherwise (see Atanassov (2013) and Chemmanur and Tian (2013) for studies on the relation between anti-takeover provisions and innovation). Our second stage results are robust to the choice of instruments: *Silicon Valley* only, *BC* only, or *Silicon Valley* and *BC* altogether.

Table X. Innovation, Hedge Fund Ownership, and Firm Value

Panel A presents OLS regression results for the following equation:

$$Q_{i,t+1} = \alpha_t + \gamma_i + \beta_1 HFH_{i,t} + \beta_2 Innovation_{i,t+1} + \beta_3 Innovation_{i,t+1} * HFH_{i,t} + \delta X_{i,t} + \varepsilon_{i,t+1},$$

where Q is Tobin's q, HFH represents hedge fund holdings, *Innovation* denotes a measure of patent quantity, citations, generality, or originality, X contains all of the control variables (LN_MV, RD_SALE, CAPX_AT, PPENT_AT, ROA, LEV, CASH_AT, Q, HI, HI2, and LN_AGE), and α_t and γ_i are year and firm fixed effects, respectively. Panel B reports the second-stage regression results of the instrumental variable (2SLS/IV) estimation, where *HFH* is instrumented by the S&P 500 inclusion dummy (S&P 500) and state intensity of hedge fund ownership (HFHState), and patent measures are instrumented by the silicon valley dummy (Silicon Valley). All of the variables are defined in Appendix B and winsorized at the upper and lower 0.25% levels. t-Statistics (in parentheses) are corrected for firm-level clustering. Intercepts and control variables are omitted for brevity.

Dep. Var.: Q_{t+1}	**LnPAT**	**LnPAT_tn**	**LnPAT_tc**	**LnCite**	**LnCite_h**	**LnCite_tn**	**LnCite_tc**	**GEN**	**GEN_tn**	**GEN_tc**	**ORG**	**ORG_tn**	**ORG_tc**
Panel A. OLS Regressions													
Patent													
Patent	0.265***	0.278***	0.480***	0.395***	0.218***	0.314***	0.300***	0.898***	0.425***	0.416***	0.428***	0.131***	0.202***
	(12.53)	(8.21)	(8.40)	(12.44)	(12.14)	(7.29)	(6.65)	(8.92)	(8.16)	(8.38)	(6.39)	(4.67)	(5.81)
HFH	0.583***	0.526***	0.492***	0.326**	0.426***	0.475***	0.455***	0.368**	0.381**	0.387**	0.571***	0.497***	0.571***
	(3.54)	(3.21)	(3.04)	(2.02)	(2.62)	(2.93)	(2.81)	(2.30)	(2.38)	(2.41)	(3.44)	(3.03)	(3.44)
Patent*HFH	0.685***	0.894***	1.673***	-0.237	0.279**	0.850***	0.702**	-0.490	0.001	0.145	1.638***	0.484***	0.841***
	(5.00)	(3.89)	(4.04)	(-0.85)	(2.01)	(2.67)	(2.12)	(-0.49)	(0.00)	(0.31)	(3.64)	(2.66)	(3.64)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.623	0.622	0.622	0.624	0.624	0.622	0.622	0.623	0.622	0.622	0.621	0.621	0.621
N	30,521	30,521	30,521	30,521	30,521	30,521	30,521	30,521	30,521	30,521	30,521	30,521	30,521
Panel B. 2SLS/IV: 2nd Stage Regression Results													
Patent(Instrumented)													
Patent	3.047	-4.933	-8.633	10.559	4.946	14.315*	13.811*	48.373	26.252	24.977	19.429*	10.435*	10.250*
(Instrumented)	(1.23)	(-0.00)	(-0.00)	(1.49)	(1.58)	(1.80)	(1.68)	(1.44)	(1.51)	(1.53)	(1.72)	(1.80)	(1.71)
HFH	7.729***	6.176***	5.840***	10.608***	10.714***	12.057***	11.055***	10.732***	11.498***	11.487***	14.064***	15.732***	14.224***
(Instrumented)	(9.75)	(7.97)	(7.76)	(11.44)	(11.88)	(13.66)	(12.47)	(11.21)	(11.88)	(11.96)	(15.32)	(16.84)	(15.51)
*Patent*HFH*	8.639***	8.784***	15.397***	43.365***	20.430***	64.215***	58.198***	208.441***	115.562***	111.741***	81.724***	46.616***	42.844***
(Instrumented)	(10.00)	(6.61)	(6.75)	(10.88)	(11.80)	(14.91)	(12.95)	(10.33)	(11.23)	(11.39)	(16.84)	(18.83)	(17.14)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.626	0.625	0.625	0.626	0.626	0.628	0.627	0.626	0.626	0.626	0.629	0.630	0.629
N	27,955	27,955	27,955	27,955	27,955	27,955	27,955	27,955	27,955	27,955	27,955	27,955	27,955

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

the leading hub of high-tech innovation and venture capital (VC) investment.[20] Silicon Valley is home to many of the world's largest technology companies, as well as thousands of small startups (SiliconValley.com), and accounts for one-third of the VC investment in the United States (PriceWaterHouseCoopers.com). Chen, Gompers, Kovner, and Lerner (2010) find that the highest concentration of VC offices is located in the San Jose/San Francisco area and more than 60% of San Jose/San Francisco firms have their VC investors in the same area. Thus, we expect firms headquartered in Silicon Valley to be more likely to have greater innovation (the relevance criterion), but there is little reason to expect the geographic location of a firm to directly affect firm value, other than through innovation (the exclusion criterion).

We estimate the two stages jointly. In the first stage, we regress *HFH* and various patent measures on their respective instruments along with the control variables. The second stage regresses Q on the predicted values of *HFH* ($\widehat{HFH}$) and patent measures ($\widehat{Patent}$) estimated from the first stage regressions and their interaction term ($\widehat{HFH} * \widehat{Patent}$). Untabulated first stage results indicate that *HFH* is still positively related to *HFHState* and negatively related to *S&P 500*, consistent with our earlier findings. Consistent with our conjecture, *Silicon Valley* is positively related to all patent measures at 1% or better significance levels. The second stage regression results in Panel B of Table X indicate that across all patent measures, $\widehat{HFH}$ is positively related to firm value. $\widehat{Patent}$ remains significant for most citations and originality measures. Controlling for endogeneity, the interaction term, $\widehat{HFH} * \widehat{Patent}$, is significantly positively related to Q across all models suggesting that hedge funds remain crucial in promoting innovation, thereby increasing firm value. In sum, our evidence suggests that hedge funds increase firm value by promoting greater innovation quantity and quality.

V. Conclusions

Using NBER patent data and a sample of hedge fund holdings of US firms from 1998 to 2006, we examine the impact of hedge fund ownership on corporate innovation. We find that hedge fund ownership increases a firm's future patent quantity and quality as proxied by patent count, citations, generality, and originality, even after controlling for endogeneity. This positive effect is stronger when hedge funds have larger holdings (i.e., blockholdings) in the firm and, as such, more effectively influence corporate managers' decisions, and when hedge fund ownership in the firm constitutes a larger proportion of total assets under management by the fund. These results are consistent with the hypothesis that hedge funds promote both quantity and quality of corporate innovation.

Further investigation reveals that hedge funds benefit innovation primarily by enhancing R&D productivity and innovation efficiency, rather than increasing R&D input. The positive effect of hedge fund ownership on innovation output and efficiency is stronger in more innovative firms, more financially constrained firms, more undervalued firms, and firms in a more competitive industry. Consequently, hedge fund ownership increases firm value via a stimulus effect on innovation.

This paper contributes to the literature regarding the effects of hedge fund ownership and identifies another channel through which hedge funds may create shareholder value. Thus, we

[20] For detailed construction of the Silicon Valley dummy, see Field et al. (2013) and Coval and Moskowitz (1999). To calculate the distance between a firm's headquarters and the center of Silicon Valley, we obtain the zip codes from the US Census Bureau's Gazetteer Place and Zip Code Database. We thank Laura Field and Michelle Lowry for graciously providing us the program and data set used in the calculation.

shed new light on the controversy concerning the role of hedge fund ownership in corporate investment decisions and shareholder value creation.

Appendix A: Patent Measures

In this appendix, we provide details regarding various measures of patent quantity, citations, generality, and originality. As noted by Hall et al. (2002) and Griliches, Pakes, and Hall (1987), the relevant year is patent application year instead of grant year as the former more accurately captures the time of the actual innovation being made and, in general, there exists a time lag of two to three years between the application and grant date.

A. Patent Quantity

PAT is the total count of patents filed by (and ultimately granted to) a firm in a calendar year. *PAT_tn* equals *PAT* divided by the average number of patents filed across all of the firms in the same application year and the same US Patent and Trademark Office (USPTO) technological class. *PAT_tc* is equal to *PAT* divided by the average number of patents filed across all of the firms in the same application year and the same Hall et al. (2002) technological category. These weighting schemes are employed to address the truncation bias in patent grants. Since an average patent has a two-year lag from the time it is filed to the time it is granted, some of the patents that have already been applied for may have not yet entered into our sample. These weighting schemes also address the concern that different industries may have different propensities for patent innovation. All three metrics capture the quantity of patents.

B. Patent Citations

While a measure of innovation, a simple count of patents does not distinguish breakthrough innovations from marginal ones. Future citations received on a patent, however, capture the value and the importance of a patent (Trajtenberg, 1990; Hall et al., 2005). *Cite* is the citations received per patent filed in a calendar year by a firm. It measures the impact of a patent (i.e., to what degree future creativity depends on it). Patent citations also suffer from truncation bias as early patents are more likely to have received more citations than patents filed and granted later. Thus, a large value of *Cite* may not necessarily represent a more important patent, but simply the artificial effect of time. Additionally, different industries may have different inclinations to cite patents. We correct for these biases by using the two methods suggested by Hall et al. (2002): 1) fixed effects and 2) the quasi-structural method. Following the fixed effects method, we construct two additional variables. *Cite_tn* (*Cite_tc*) is equal to *Cite* divided by the total number of citations received on all of the patents filed in the same USPTO class (Hall et al., 2002 technological category) for the same application year. We also employ the quasi-structural method and multiply each patent citation by an index estimated econometrically from the distribution of the citation lag between the application and grant date as in Hall et al. (2002) (*Cite_h*).

C. Patent Generality

Although citations per patent help to gauge the general impact of patented research on future innovations, they do not provide detailed information regarding the distribution of this impact. A variety of citation-based metrics can be constructed to examine different aspects of the patented innovation and its relationship to other innovations. Patent generality is defined as a Herfindahl concentration index that measures how broadly this patent impacts future innovations (Trajtenberg et al., 1997). For example, if a patent receives citations by subsequent patents that span a wide range of technical classes, this measure will be high suggesting a broader contribution of the patented innovation to future ones. In contrast, patent generality will be low if most citations are concentrated in a small number of fields and the patent's contribution is more focused in certain areas. Following Trajtenberg et al. (1997), Hall et al. (2002), and Hall (2005), we construct three measures of patent generality. *GEN* is the average generality score across all patents filed by a firm in a calendar year, where the generality score for each patent is constructed using USPTO technological classes as follows and is bias-corrected as in Hall (2005):

$$Generality_i = 1 - \sum_{j}^{n_i} S_{ij}^2, \tag{A.1}$$

where S_{ij} denotes the percentage of citations received by patent i that belongs to patent class j, out of n_i patent classes. Note that the sum is the Herfindahl index. Thus, *Generality* is the opposite of the Herfindahl index. *GEN_tn* (*GEN_tc*) is constructed analogously except that the generality score for each patent is scaled by the average generality of all of the patents filed in the same USPTO (Hall et al., 2002) class for the same application year to correct for truncation bias in citation data.

D. Patent Originality

While the forward citation measures, such as *Cite* and *GEN*, gauge the influence of the patent on future descendants (or, put differently, the social returns to innovation), they are not informative regarding the nature of the innovation. Patent originality captures how original or radical a patent is relative to its predecessors. A patent is considered original or breakthrough if it cites previous patents that belong to a wide range of fields (high originality), and incremental if the patented invention builds on a narrow set of technologies (low originality). Originality is constructed in the same manner as generality in Equation (A.1), except that originality refers to citations made rather than received. Following Trajtenberg et al. (1997), Hall et al. (2002), and Hall (2005), we construct three measures of patent originality. *ORG* is the average originality scores across all patents filed by a firm in a calendar year, where the originality score for each patent is constructed using USPTO class and bias-adjusted as in Hall (2005). *ORG_tn (ORG_tc)* is constructed similarly, except that the originality score for each patent is scaled by the average originality of all of the patents filed in the same USPTO (Hall et al., 2002) class and application year.

Appendix B: Variable Definitions

Variable	Definition
	Panel A. Measures of Innovation and Innovation Efficiency in Application Year t+1
PAT	The total number of patents filed by (and ultimately granted to) firm i in year $t+1$.

(*Continued*)

Appendix B (*Continued*)

Variable	Definition
PAT_tn	The total number of patents filed by (and ultimately granted to) firm *i* in year *t*+1, scaled by the average number of patents filed across all firms in the same USPTO technological class and application year *t*+1.
PAT_tc	The total number of patents filed by (and ultimately granted to) firm *i* in year *t*+1, scaled by the average number of patents filed across all firms in the same Hall et al., (2002) technological category and application year *t*+1.
LnPAT	Natural logarithm of one plus *PAT*.
LnPAT_tn	Natural logarithm of one plus *PAT_tn*.
LnPAT_tc	Natural logarithm of one plus *PAT_tc*.
Cite	The number of citations received per patent filed by (and ultimately granted to) firm *i* in year *t*+1.
Cite_h	The number of citations received per patent filed by (and ultimately granted to) firm *i* in year *t*+1, multiplied by an index estimated econometrically from the distribution of the citation lag between the application and grant date as in Hall et al. (2002) (i.e., the quasi-structural method).
Cite_tn	The number of citations received per patent filed by (and ultimately granted to) firm *i* in year *t*+1, scaled by the total number of citations received for all patents filed in the same USPTO technological class and application year *t*+1.
Cite_tc	The number of citations received per patent filed by (and ultimately granted to) firm *i* in year *t*+1, scaled by the total number of citations received for all patents filed in the same Hall et al. (2002) technological category and application year *t*+1.
LnCite	Natural logarithm of one plus *Cite*.
LnCite_h	Natural logarithm of one plus *Cite_h*.
LnCite_tn	Natural logarithm of one plus *Cite_tn*.
LnCite_tc	Natural logarithm of one plus *Cite_tc*.
GEN	Average generality score across all patents filed by firm *i* in year *t*+1, where the generality score for each patent is constructed using USPTO technological classes and bias-corrected as in Hall et al. (2002).
GEN_tn	Average generality score across all patents filed by firm *i* in year *t*+1, where the generality score for each patent is scaled by the average generality of all patents filed in the same USPTO technological class and application year *t*+1.
GEN_tc	Average generality score across all patents filed by firm *i* in year *t*+1, where the generality score for each patent is scaled by the average generality of all patents filed in Hall et al. (2002) the same technological category and application year *t*+1.
ORG	Average originality score across all patents filed by firm *i* in year *t*+1, where the originality score for each patent is constructed using USPTO technological classes and bias-corrected as in Hall, et al. (2002).
ORG_tn	Average originality score across all patents filed by firm *i* in year *t*+1, where the originality score for each patent is scaled by the average originality of all patents filed in the same USPTO technological class and application year *t*+1.
ORG_tc	Average originality score across all patents filed by firm *i* in year *t*+1, where the originality score for each patent is scaled by the average originality of all patents filed in the same Hall et al. (2002) technological category and application year *t*+1.

(*Continued*)

Appendix B (*Continued*)

Variable	Definition
$Ln\left(\frac{1+PAT_{t+1}}{1+R\&D_t}\right)$	Natural logarithm of the ratio of one plus the total number of patents filed by firm *i* in application year *t*+1 to one plus R&D expenditures (in $000's) in year *t*.
$Ln\left(\frac{1+AllCites_{t+1}}{1+R\&D_t}\right)$	Natural logarithm of the ratio of one plus the total number of citations received in life on patents filed by firm *i* in application year *t*+1 to one plus R&D expenditures (in $000's) in year *t*.
Panel B. Hedge Fund Ownership at the End of Year t	
HFH	The sum of shares held by the sample hedge funds divided by the total number of shares outstanding for firm *i* at the end of year *t*.
ΔHFH	The annual change in *HFH* from year *t*-1 to *t* prior to patent application year *t*+1.
Panel C. Control Variables at the End of Fiscal Year t	
MV	Market value of equity = share price times the number of shares outstanding [#25∗#199].
AT	Total assets [#6].
Sales	Total sales [#12].
LN_MV	Natural logarithm of MV.
LN_AT	Natural logarithm of AT.
LN_Sales	Natural logarithm of Sales.
RD_AT	Research and development expenditures over total assets [#46/#6].
RD_Sale	Research and development expenditures over total sales [#46/#12].
CAPX_AT	Capital expenditures over total assets [#128/#6].
PPENT_AT	Net property, plant, and equipment over total assets [#8/#6].
ROA	Return on assets, defined as operating income before depreciation over total assets [#13/#6].
LEV	Book value of debts over book value of total assets [(#34+#9)/#6].
CASH_AT	Cash over total assets [#1/#6].
Q	Tobin's *q*, defined as the market value of assets over the book value of total assets [(#6-#60+abs(#25∗#199))/#6].
HI	Herfindahl index based on sales of the four-digit SIC industry to which the firm belongs.
HI2	The square of HI.
AGE	Firm age, measured as the number of years listed in CRSP.
LN_AGE	Natural logarithm of one plus AGE.
Panel D. Instrumental Variables at the End of Year t	
S&P 500	S&P 500 inclusion dummy that is equal to one if the firm is included in the S&P 500 index in year *t* and zero otherwise.
HFHState	State density of hedge fund ownership, defined as the proportion of the total market capitalization of firms headquartered in a state that are held by the sample hedge funds (regardless of their geographic locations) in year *t*.
Silicon Valley	Silicon Valley dummy that is equal to one if the firm's headquarters is located within 100 km of the center of Silicon Valley and zero otherwise.

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