SIER Working Paper Series No. 105

Market Value of Patents: Evidence from the US, 1976-2017

By

Jihong Lee and Hyunkyeong Lim

January, 2019

Institute of Economic Research
Seoul National University

Market Value of Patents: Evidence from the US, 1976-2017*

Jihong Lee†
Seoul National University

Hyunkyeong Lim‡
Seoul National University

January 2019

Abstract

Since the 1980s, the US has experienced a surge in patenting and R&D. To better understand the phenomena, we explore the evolution of the market value of knowledge capital with a novel firm-level dataset. While the importance of R&D has steadily declined, the market value of patents made a large and sustained gain in the new millennium. An additional patent per million dollars of R&D improves firm value by 11% in the latest decade compared to 3% three decades ago. The increased patent rents are driven largely by young firms, suggesting a positive role of the US patent system.

Keywords: Innovation, firm value, patent, R&D

JEL codes: O31, O34, O38, G30

*The authors thank Bronwyn Hall, Jungmin Lee, Simon Lee, Yoon-Jae Whang, and seminar participants at the Korea Development Institute for helpful comments. This research was supported by the Park Yang Sook-Chung Yung Ho fund at Seoul National University and a National Research Foundation Grant funded by the Ministry of Education of Korea (NRF-2017S1A5A2A01023849).

†Department of Economics, Seoul National University, Seoul 08826, Korea; jihonglee@snu.ac.kr

‡Department of Economics, Seoul National University, Seoul 08826, Korea; hklim0430@snu.ac.kr

1. Introduction

Patenting in the US embarked on a remarkable rise in the 1980s. The timing coincided with several policy shifts that served to strengthen the rights of patent holders and reduce the cost of acquisition. With the surging number of patents, new cases of dubious inventions surfaced as well as a burgeoning industry of patent trolls and litigations. These developments were naturally alarming and even prompted some critics to call the US patent system "broken" (e.g. Jaffe and Lerner, 2004; Boldrin and Levine, 2008; Bessen and Meurer, 2008).[1]

The patent surge, if anything, has gained further momentum in the new millennium. Between 2006 and 2015, the US Patent and Trademark Office (USPTO) issued more than 2 million utility patents, almost as many as the preceding two decades combined. At the same time, US firms' patent yield on R&D spending has declined. If the patent system were malfunctioning, one possible explanation for these stylized facts would be falling quality and value of patents together with profit-maximizing firms diverting R&D resources for trade secrets and other non-patentable inventions.

Innovation is a complex phenomenon, and the patent system must deal with multiple trade-offs. But, the fundamental policy parameter is the value of economic *rent* that a patent generates. Without these supra-normal profits, the public good nature of innovation would mean under-provision; too much of it would entail excessive loss of consumer surplus and delay of new technological breakthroughs. In light of the rapidly changing climate for R&D and patenting activities, this paper aims to study the evolution of economic rents associated with US patents.

Following the literature initiated by Griliches (1981), we explore the *market value* of patent rents.[2] Our model specification adopts that of Hall, Jaffe, and Trajtenberg (2005), henceforth HJT, who decompose market value (or Tobin's Q) of a firm into multiple indicators of its *knowledge stock*.[3] We estimate the model using a novel firm-level dataset that matches assignees of US patents to

[1] Kortum and Lerner (1999) analyze the rising number of US patents in the 1980s. For a recent discussion of the patent system, see the winter 2013 symposium of *Journal of Economic Perspectives*.

[2] See Hall (2000) for a review of this literature.

[3] Our focus is however different from HJT, whose main finding is the role of patent *citations* as a further indicator of firm value.

firms listed in Compustat for the period of January 1976 to December 2017.[4]

The hedonic panel regressions are conducted for multiple cohorts within the sample period. The overall goodness of fit remains relatively stable across the cohorts and all the main regressors are statistically significant in every cohort considered. We observe the following trends in the relative importance of the knowledge stock variables.

First, the importance of R&D intensity has declined steadily. Second, the shadow value of patent per R&D fell initially in the 1990s, to about a half of the value in the 1980s, but made a large and sustained gain in the new millennium. Third, citations have become less important. Also, though in different degrees, these trends appear across sectors.

Taken together, our evidence suggests that the surge in patenting and R&D spending per patent reflects increased market value of patents. The US patent system, after a blip in the 1990s, has become ever so successful in providing incentives for innovation measured by patents. According to our estimation, on average, an additional patent per million dollars of R&D boosts firm value by as much as 11% in the latest decade compared to just over 3% three decades ago. Any inefficiency in the system, then, would likely be in *over*protection of private rents.

One particular concern is that stronger patent rights may increase patenting, not innovation. For instance, the broadened scope of patentability has been criticized for creating patent portfolio *races* and deadweight losses in hitech industries (e.g. Shapiro, 2000; Hall and Ziedonis, 2001). Patenting and productivity growth also remain weakly related (e.g. Boldrin, Allamand, Levine, and Ornaghi, 2011).[5] To weigh in on this issue, we draw an idea from the endogenous growth theory.

The basic assumption, formalized by Klette and Kortum (2004) and others, is that new entrants must be inventive to come into existence and to survive. Indeed, young firms account for a large proportion of job growth (e.g. Haltiwanger, Jarmin, and Miranda, 2013), have higher productivty (e.g. Foster, Haltiwanger, and Syverson, 2008) and spend more on R&D per sales (e.g. Acemoglu,

[4]We build on the NBER Patent Data Project (PDP) which offers the corresponding matching up to 2006. Latest parent-subsidiary relationships are incorporated by additional matching of the LexisNexis Corporate Hierarchy database.

[5]Bloom and Van Reenen (2002) suggest a lagged impact of patents on firm productivity. Griliches (1994) points to measurement difficulties.

Akcigit, Alp, Bloom, and Kerr, 2018) than mature firms.

We therefore assess the value of patents to young firms. It turns out that, except for the 1990s, the market value of young firms is more strongly correlated with their patents than the rest of sample firms. Moreover, the magnitude of these effects is highest during the early parts of the millennium, precisely the period of rapid growth in overall patent value. These findings suggest that, at the very least, the US patent system has been playing a positive role for innovation and success of entrant firms.

The literature on innovation and market value is large but has been thus far confined mostly to pre-2000 years, presumably due to lack of latest firm-level data. Our study demonstrates an important gap in the literature. The patent surge began in the 1980s but the data constructed and used by HJT (2001, 2005), later extended to 2006 by NBER PDP, would not have picked up the long-run rise of patent value that took off in the 2000s. This has been uncovered by our matching of additional 11 years worth of patents and assignees to Compustat.

Our paper complements studies that employ alternative methods of measuring patent value. One line of research beginning with Pakes and Schankerman (1984) exploits the observed behavior of patent holders, such as whether to pay renewal fees. Other methods include using survey to elicit inventors' view of patent value (e.g. Harhoff, Narin, Scherer, and Vopel, 1999; Gambardella, Harhoff, and Verspagen, 2008) and constructing quality index with various patent statistics (e.g. Lanjouw and Schankerman, 2004). A recent paper by Kogan, Papanikolaou, Seru, and Stoffman (2017) finds the value of patent by measuring the stock market response to its news.[6] Note that, in contrast to our firm-level methodology, these papers estimate rents at the patent-level.

While patents could serve a range of functions for young firms, a growing body of literature has focused on improved financing facilitated by patent portfolios (see Hall (2018) for a review).[7] Some of these studies consider the effect of patents on the firms' valuation at IPO or other financing stages, and find evidence of a positive causal relationship (e.g. Lerner, 1994; Hsu and Ziedonis, 2013; Greenberg, 2013). Patents also increase the likelihood of startups going public (e.g. Cockburn and MacGarvie, 2009). In this paper, we examine the

[6]Kogan *et al.* (2017) find patents that can be matched to stock market data up to 2010. We have benefited also from their data construction procedures.

[7]See also Graham, Merges, Samuelson, and Sichelman (2009) who survey young technology startups.

market value of young, listed firms.

The rest of the paper is organized as follows. We begin by introducing the framework of our estimation model in Section 2. Section 3 then describes our dataset that matches USPTO assignees to Compustat firms over the period 1976-2017. Our main findings on the trends of the market value of various knowledge stocks are presented in Section 4, followed by the results on young firms in Section 5. We address several robustness concerns in Section 6 and offer some concluding remarks in Section 7. Appendices contain a detailed description of our data construction as well as some results left out from the main text for expositional reasons.

2. Analytic Framework

Griliches (1981) proposes the following linear and additively separable market value equation: for firm i and time t,

$$V_{it} = \alpha_t \left(A_{it} + \beta_t K_{it}\right)^{\sigma}, \tag{1}$$

where

- V_{it} is the market value;
- A_{it} is the stock of physical assets;
- K_{it} is the stock of knowledge assets;
- α_t represents the shadow value of all assets, equalized across firms;
- β_t represents the shadow value of knowledge assets relative to physical assets;
- σ is a parameter representing scale effects.

Assuming constant returns to scale (i.e. $\sigma = 1$) and taking logarithm of (1), we derive an equation for Tobin's Q:

$$\log Q_{it} := \log\left(\frac{V_{it}}{A_{it}}\right) = \log \alpha_t + \log\left(1 + \beta_t \frac{K_{it}}{A_{it}}\right). \tag{2}$$

HJT proxies the knowledge-physical capital ratio, K_{it}/A_{it}, with three components and estimate the equation below:

$$\log Q_{it} = \log \alpha_t + \log \left(1 + \beta_{1t}\frac{RD_{it}}{A_{it}} + \beta_{2t}\frac{PAT_{it}}{RD_{it}} + \beta_{3t}\frac{CITES_{it}}{PAT_{it}}\right) + \varepsilon_{it}, \quad (3)$$

where

- RD_{it} is the stock of R&D expenditure by firm i up to, and including, time t;
- PAT_{it} is the stock of patents granted to firm i up to, and including, time t;[8]
- $CITES_{it}$ is the stock of forward citations received by firm i's stock of patents at time t.

R&D expenditure reflects the firm's overall innovation effort, while patents and citations respectively offer measures of the *success* and *quality* of the effort.

The stock variables are computed as follows. For a given stock X_t at time $t > 0$, let x_t denote the corresponding *flow*. Then, we can recursively define X_t as

$$X_t = (1 - \delta)X_{t-1} + x_t,$$

where $\delta \in (0, 1)$ is the depreciation rate and $X_0 = x_0$ is the initial value. For RD_{it} and PAT_{it}, the flow terms are simply the R&D expenditure spent by and the number of patents granted to firm i in period t. For $CITES_{it}$, the flow term counts the total number of forward citations that all patents granted to firm i in period t receive over a fixed number of periods in and after t.

3. Data

Our analysis is based on construction of a large-scale dataset that merges USPTO data with Compustat firm data. We consider all utility patents granted by USPTO between January 1976 and December 2017 and all firms included in the Computat database over the period 1960-2017. The USPTO bulk data in our sample contain 347909 assignees with 5195042 patents granted to them; the Compustat database includes 38554 firms with unique identifiers.

[8]Our main messages are unaffected by computing the patent stock in terms of *application* date. See Section 6 for a discussion.

We build on the work of NBER Patent Data Project (PDP). By modifying and improving their algorithms we first standardize assignee/firm names and then match them across the two datasets. Also, new parent-subsidiary relationships are added by invoking the 2018 edition of LexisNexis Corporate Hierarchy Database.

The end product is a list of 9517 US-based publicly traded firms, each with financial and patent data over 1976-2017. It covers 1871238 patents representing about 36% of all assigned patents granted during the sample period. Our dataset includes firms across *all* sectors, and not just the manufacturing sector as considered by HJT for their estimation. A detailed description of the matching process is provided in Appendix A.

Using the matched dataset, we estimate equation (3) and its variants over multiple cohorts within the sample period to scrutinize the trends in market value of each component of knowledge capital. Our main analysis considers four cohorts: 1979-1988, 1989-1998, 1999-2008, and 2009-2017.[9] For each cohort, we include every firm that has at least one patent granted within the corresponding years. Panel regression is conducted over the pooled data for each cohort with year dummies.[10]

Tobin's Q is calculated annually according to the formula of Gompers, Ishii, and Metrick (2003):

$$Q := \frac{\text{Market value}}{\text{Replacement cost of capital}},$$

where

- the replacement cost of capital is approximated by the book value of assets;
- the market value is approximated by the sum of the market value of common stock and the book value of assets less the sum of the book value of common stock and balance sheet deferred taxes.[11]

This formula, readily computable from Compustat data, is based on a simplified

[9]The first cohort is chosen to match HJT's main analysis. As a result, the final cohort, 2009-2017 is one year shorter than the others.

[10]As in HJT, we do not include firm fixed effects. R&D decisions typically change slowly and are highly correlated with permanent individual traits.

[11]In Compustat terms, $Q = \frac{CSHO \times PRCC\_C + AT - (CEQ + TXDB)}{AT}$.

proxy for the replacement cost of capital. Also, it assumes the market value of preferred stock and debt to equal book value.[12] Our results are robust to using a more extensive estimate of Tobin's Q. See Section 6.

The three stock variables, RD, PAT, and $CITES$, are all constructed with a 15% depreciation rate, as in HJT, and the initial values are set for years 1976, 1986, 1996, and 2006 for the four cohorts 1979-1988, 1989-1998, 1999-2008, and 2009-2017, respectively.

The initial stock of R&D is calculated by dividing the first year's R&D expenditure by the sum of the depreciation rate and a pre-sample growth rate of R&D assumed to be 8% as in Hall (1990). For the subsequent R&D stocks, previous year's stock is adjusted using Bureau of Economic Analysis (BEA) R&D deflators (with 2012 as the base year) as well as the depreciation rate.[13] For $CITES$, we count forward citations over fixed 10-year window to avoid the truncation issue. Our estimation for the final 2009-2017 cohort does not include $CITES$ as explanatory variable.[14]

Figure 2 plots yearly patent counts and citations. The left panel shows the annual number of patents granted to US assignees and also to the subset of those matched to Compustat. Patenting has indeed intensified since the 1980s, and moreover, the pace of greater patenting further accelerated in the last 10 years.

With more patents, the number of citations has also increased. In the right panel of Figure 1, we present annual trends in average number of citations received by all the patents granted to matched assignees as well as to all US assignees over 10-year window. Here, we witness 10-year average citation rising rapidly up to the early 2000s, although there are some signs of tailing off since then. The truncation issue is reflected at the right end of each panel.

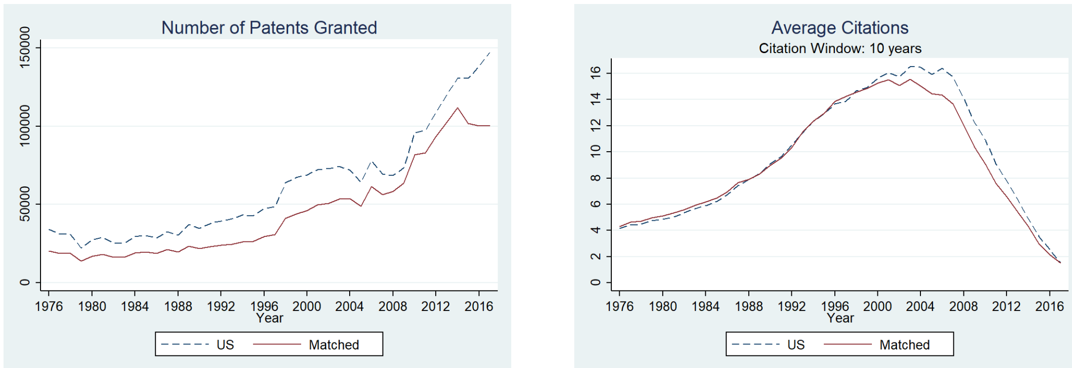
Table 1 summarizes basic descriptive statistics for the main variables used in the estimation analysis. Missing Compustat values are linearly interpolated using `ipolate` in STATA, except cases in which all relevant items are missing for the given year. From each cohort, we exclude firms that report null value in

[12]Note that the book value of assets is the sum of the book value of common stock and the book value of preferred stock and debt.

[13]The unit of R&D spending and other monetary variables is million dollars.

[14]Our construction of patent-related variables somewhat differs from HJT who, in particular, considers citation stocks based on application dates and estimates citation lags over 30-year window. Note that our focus is to observe how the coefficient estimates evolve over time.

Figure 1



every item for at least one year.[15] There are still firm-year observations with zero R&D stock. In these cases, following HJT, we treat the corresponding PAT/RD variable also as zero and include a dummy in the regression.[16]

Table 1: Sample Statistics

Variable	Description	Cohort											
		1979-1988			1989-1998			1999-2008			2009-2017		
		Mean	Median	Std.Dev.	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
V	Market Value ($M)	1451.05	111.17	6488.45	3664.83	190.80	17691.99	11793.34	479.98	73922.26	24485.94	1203.76	148056.70
A	Book Value ($M)	1229.03	90.15	5895.94	2382.03	107.20	12929.16	8383.45	248.86	67768.28	19176.12	593.42	143536.50
Q	Tobin's Q	1.93	1.17	18.19	3.11	1.54	26.39	5.62	1.70	76.08	6.34	1.73	124.07
RD[1]	R&D stock ($M)	172.13	12.07	822.24	381.38	25.08	2067.68	725.71	69.16	3243.70	1395.37	131.42	5280.32
PAT	Patent stock	45.08	3.23	206.95	48.54	3.26	299.10	83.97	4.58	552.79	160.11	7.59	987.35
$CITES$[2]	Citation Stock	232.52	16.18	1239.70	515.38	31.46	3526.93	1127.21	61.91	7712.98			
RD/A		0.26	0.10	3.95	1.43	0.17	79.22	1.85	0.23	40.03	1.55	0.20	17.56
PAT/RD[1]		1.21	0.49	3.83	0.80	0.24	6.92	0.48	0.14	2.94	0.40	0.12	2.95
$CITES/PAT$		5.00	3.73	5.56	11.87	7.63	15.29	17.80	9.63	27.53			
Number of patenting firms			2095			2923			3605			2966	
Number of observations			12288			16440			22122			17564	

[1] For 9011 obs (1979-1988), 12613 obs (1989-1998), 17646 obs (1999-2008), and 13527 obs (2009-2017) with $RD > 0$.
[2] For 11775 obs (1979-1988), 16158 obs (1989-1998), and 21782 obs (1999-2008) with $CITES > 0$.

All the variables exhibit skewness in every cohort, as expected. For both market and book values, and the three knowledge stocks, the skewness is extreme throughout. In the cases of Tobin's Q and the three ratios, RD/A, PAT/RD, and $CITES/PAT$, the mean-median difference is not as stark but has risen since the earliest cohort.

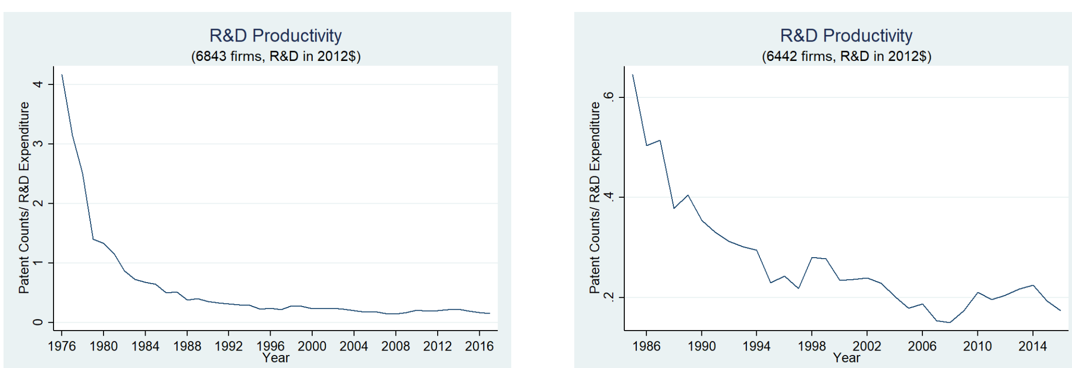
[15]For the four cohorts in chronological order, 31, 57, 75, and 25 patenting firms are excluded as a result.
[16]The number of such observations are 2712, 3442, 4064, and 3734 in the four cohorts.

Market and book values, as well as the knowledge stocks, have grown substantially over the years. The level of R&D stock roughly doubled every decade but for the patent stock similar jump occurred only after the 1990s. Average Tobin's Q in 2009-2007 is also more than three times that of 1979-1988.

Looking at the explanatory variables in our regression, R&D intensity (RD/A) rapidly went up in the 1989-1999 cohort, followed by a relatively small gain in 1999-2008 and then a loss in 2009-2017. Average quality of patent stock ($CITES/PAT$) also increased. Importantly, we observe steady decline in R&D productivity (PAT/RD). The growth of R&D stocks of US firms has outpaced their patent stocks.

To elaborate upon the last observation above, we also consider R&D productivity in terms of flow. Figure 2 presents the total number of patents granted per *real* R&D spending each year for firms that appear in our estimation analysis at least once. The left panel contains the entire sample period 1976-2017, while the right panel highlights 1985-2017. R&D productivity fell precipitously in late 1970s, and the decline more or less continued until recently. US firms have indeed been pouring investment into R&D despite receiving less and less in return for every dollar spent.

Figure 2



4. Estimation Results

We estimate the market value equation (3) and its variants using non-linear least squares. Given the truncation issue, the panel regression for the final cohort (2009-2017) does not involve citations as explanatory variable. We are primarily interested in differences across periods, and running the regressions for the other cohorts without citation stock does not alter the estimates greatly. Whenever $CITES/PAT$ is included as regressor, we run an additional regression by breaking the variable into five groups with the bottom quarter serving as the base category, as in HJT. We also estimate the model over 5-year cohorts, which are reported in Appendix B (Tables 9 and 10).[17]

Market Value of R&D and Patent Stocks Our main concern is the economic rents associated with US patents. To obtain and evaluate the latest estimate, our main estimation considers only RD/A and PAT/RD as regressors, and the results are presented in Table 2. The overall explanatory power of the regression remains relatively stable with R^2 ranging between 0.23 and 0.27. Both knowledge capital variables are statistically significant predictors of firm value in every cohort. We detect shifts in relative importance of the two factors by comparing coefficient estimates across cohorts.

First, although R&D intensity contributes most to firm value, its coefficient estimate has declined by a significant margin. The fall was rapid moving from 1979-1988 to 1989-1998, as the estimate decreased by more than half, from 1.334 (column 1) to 0.597 (column 2). It fell further to 0.394 (column 3) in the 1999-2008 cohort but then stabilized to 0.395 in 2009-2017 (column 4). The last figure is just 30% of the corresponding estimate for 1979-1988.

In sharp contrast, the market value of patents has increased dramatically following a decline in the 1990s. The coefficient estimate for patent yield per million dollars of R&D stock in 1979-1988 is 0.036; it goes down to 0.017 in 1989-1998 but then rises to 0.089 in 1999-2008 and to 0.109 in 2009-2017. The last figure represents a three-fold increase from the 1980s.

The dummy estimate for firms that do not engage in R&D is positive and significant in the 1979-1988 cohort, which is in line with HJT's finding. It however becomes negative in the two subsequent cohorts and barely positive (and statistically insignificant) in the latest cohort.

Although the rise of patenting began in the 1980s, its importance in terms of market value fell initially in the 1990s.[18] Our new dataset however reveals that

[17]The initial year for the stock variables are adjusted accordingly.

[18]Why this happened in the 1990s poses an interesting question. Notice from Table 1 that,

Table 2: Market Value of R&D and Patent Stocks

Variable	Cohort 1979-1988	1989-1998	1999-2008	2009-2017
	(1)	(2)	(3)	(4)
RD/A	1.334***	0.597***	0.394***	0.395***
	(0.071)	(0.029)	(0.016)	(0.017)
PAT/RD	0.036***	0.017**	0.089***	0.109***
	(0.006)	(0.005)	(0.014)	(0.017)
$D(RD = 0)$	0.077***	-0.070***	-0.078***	-0.011
	(0.014)	(0.013)	(0.014)	(0.016)
#Firms	2095	2923	3605	2966
#Observations	12288	16440	22122	17564
R^2	0.242	0.234	0.264	0.265
Standard Error	0.503	0.618	0.713	0.698

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.
$^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

the continued surge in patenting and R&D spending per patent by US firms is associated with rapid growth in patent rents on the one hand and steady decline in the shadow value of R&D on the other. The latter suggests diminishing returns.

Citations How has the market been valuing the quality of patents? Table 3 presents the results from estimating the full specification of (3) including $CITES/PAT$. The coefficient estimate for the average quality of patent stock has also declined steadily, and the market now appears to value a firm's patent stock far more than its citations. Recall that patents receive more citations now than previously, and similarly to R&D, there could be diminishing marginal re-

although the mean and median values of PAT/RD in the 1989-1998 sample are lower than in 1979-1988, the standard deviation is much larger.

turn in play for citations.

In the 1979-1988 cohort, the contribution of patent quality to firm value is not too different from that of patent count (0.027 vs. 0.039).[19] But, by 1999-2008, the difference becomes more than 13 times (0.008 vs. 0.109). Inclusion of citation dummies shows that the market value of citation increases with the firm's level of average citation stock. Our analysis also shows that this pattern has intensified over the years.

Semi-elasticities Estimates of the quantitative impact of each regressor can be computed from the estimated coefficients and sample values of the regressors via the following partial derivative:

$$\frac{\partial \log Q}{\partial Y} := \hat{\beta}_Y \left(1 + \hat{\beta}_{RD/A}\frac{RD}{A} + \hat{\beta}_{PAT/RD}\frac{PAT}{RD} + \hat{\beta}_{CITES/PAT}\frac{CITES}{PAT}\right)^{-1}, \quad (4)$$

where $Y \in \{RD/A, PAT/RD, CITES/PAT\}$ and, with slight abuse of notation, $\hat{\beta}_Y$ is the estimated coefficient value for variable Y.

Table 4 reports semi-elasticities calculated with the estimates from Table 2 (see also Table 11 in Appendix B). Given their high skewness, the variables in the right-hand side of (4) are evaluated at the mean, median, and ratio of totals from the actual observations in each cohort.

Considering the totals, on average, an additional patent per million dollars of R&D boosts firm value by as much as 11% in 2009-2017 compared to slightly more than 3% three decades ago. The impact of a one-percentage point increase in R&D intensity in 2009-2017 (0.38%) is about one third of the corresponding figure in 1979-1988 (1.16%).

Industry Effects We adopt the Global Industry Classification Standard (GICS) by Standard & Poor's and divide the set of firms into the following six sectors:

- Materials, Industrials, Consumer Discretionary, Health Care, Information Technology, and Others.[20]

[19] HJT finds the coefficient of $CITES/PAT$ to be greater than that of PAT/RD in their estimation of the same cohort. Recall that our estimation differs from HJT in a number of ways, including the spectrum of industries considered.

[20] "Others" include all the remaining sectors (Energy, Consumer Stapes, Financials, Telecommunication Services, Utilities, and Real Estate) as well as firms unassigned to any sector.

Table 3: Market Value of Knowledge Stocks with Citations

Variable	Cohort 1979-1988		1989-1998		1999-2008	
	(1)	(2)	(3)	(4)	(5)	(6)
RD/A	1.388***	1.179***	0.617***	0.501***	0.437***	0.378***
	(0.079)	(0.069)	(0.033)	(0.028)	(0.018)	(0.016)
PAT/RD	0.039***	0.036***	0.019**	0.018***	0.109***	0.100***
	(0.007)	(0.006)	(0.006)	(0.005)	(0.016)	(0.014)
$CITES/PAT$	0.027***		0.017***		0.008***	
	(0.002)		(0.001)		(0.001)	
$D(RD=0)$	0.096***	0.078***	-0.035**	-0.051***	-0.050***	-0.054***
	(0.014)	(0.014)	(0.013)	(0.012)	(0.014)	(0.014)
Citation Dummies[1]						
$D1$[2]		-0.062***		-0.010		0.046***
		(0.012)		(0.013)		(0.013)
$D2$[3]		-0.006		0.090***		0.100***
		(0.014)		(0.015)		(0.014)
$D3$[4]		0.135***		0.228***		0.208***
		(0.016)		(0.016)		(0.015)
$D4$[5]		0.283***		0.451***		0.438***
		(0.031)		(0.029)		(0.032)
#Firms	2095	2095	2923	2923	3605	3605
#Observations	12288	12288	16440	16440	22122	22122
R^2	0.261	0.265	0.266	0.262	0.283	0.280
Standard Error	0.497	0.496	0.605	0.607	0.703	0.705

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.
[1] Baseline group: 0-2 (2602 obs), 0-4 (3729 obs), 0-5 (5262 obs) for each cohort in order.
[2] 3-4 (4216 obs), 5-8 (4891 obs), 6-10 (6194 obs) for each cohort in order.
[3] 5-6 (2560 obs), 9-14 (3720 obs), 11-20 (5245 obs) for each cohort in order.
[4] 7-13 (2298 obs), 15-35 (3269 obs), 21-60 (4295 obs) for each cohort in order.
[5] >13 (612 obs), >35 (831 obs), >60 (1126 obs) for each cohort in order.

Table 4: Semi-elasticities

	Cohort											
	1979-1988			1989-1998			1999-2008			2009-2017		
Ratios Evaluated at the:	Mean	Median	Total	Mean	Median	Total	Mean	Median	Total	Mean	Median	Total
RD/A	0.26	0.10	0.10	1.43	0.17	0.12	1.85	0.23	0.07	1.55	0.20	0.06
PAT/RD	0.89	0.26	0.36	0.62	0.13	0.17	0.39	0.09	0.14	0.31	0.07	0.15
Semi-elasticities[1]												
$\frac{\partial logQ}{\partial(RD/A)}$	0.970***	1.163***	1.160***	0.321***	0.540***	0.554***	0.224***	0.359***	0.379***	0.240***	0.365***	0.381***
	(0.038)	(0.054)	(0.054)	(0.008)	(0.023)	(0.025)	(0.005)	(0.013)	(0.015)	(0.007)	(0.015)	(0.016)
$\frac{\partial logQ}{\partial(PAT/RD)}$	0.026***	0.032***	0.032***	0.009**	0.016**	0.016**	0.051***	0.081***	0.086***	0.066***	0.100***	0.105***
	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.007)	(0.012)	(0.013)	(0.010)	(0.016)	(0.016)

[1] Computed using the estimated coefficients of Table 2.
Heteroskedastic-consistent standard errors are shown in parentheses.

The number of firms and observations for each sector are summarized in Table 5, where we observe notable growths of Health Care and Information Technology.

Table 5: Observations and Firms by Industry & Cohort

	Cohort							
	1979-1988		1989-1998		1999-2008		2009-2017	
Industry Sector (GICS[1] Code)	Obs	Firms	Obs	Firms	Obs	Firms	Obs	Firms
Materials (15)	1364	194	1587	239	1514	222	1078	158
Industrials (20)	3161	460	3616	564	3557	525	2683	395
Consumer Discretionary (25)	1914	293	2068	372	2238	381	1749	285
Health Care (35)	1161	220	3129	618	5315	882	4720	900
Information Technology (45)	2448	417	4208	829	6899	1174	4849	822
Others (0,10,30,40,50,55,60)[2]	2240	511	1832	301	2599	421	2485	406
Total	12288	2095	16440	2923	22122	3605	17564	2966

[1] Global Industry Classification Standard
[2] 0=unassigned firms

In Table 6, we summarize the estimation results with industry dummies for the model with only RD/A and PAT/RD as regressors. See Appendix B (Table 12) for the results with $CITES/PAT$.

Columns 2, 5, 8, and 11 report estimation results just with dummies for the six sectors. Here, for every cohort, we see a market value premium for firms in the Health Care sector, and this is accompanied by smaller coefficients for

Table 6: Industry Effects

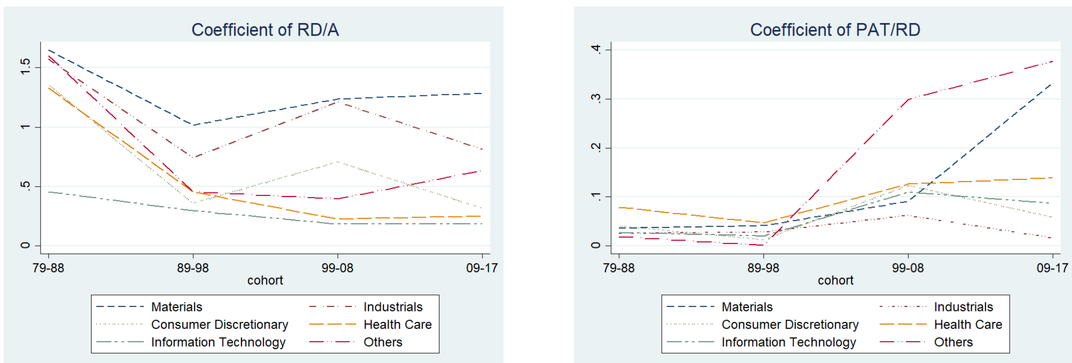
Variable	Cohort											
	1979-1988			1989-1998			1999-2008			2009-2017		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$D(Materials)$		-0.059***	-0.068***		-0.138***	-0.205***		-0.165***	-0.204***		0.136***	0.047
		(0.014)	(0.019)		(0.018)	(0.024)		(0.018)	(0.021)		(0.025)	(0.034)
$D(Industrials)$		0.027*	0.019		-0.115***	-0.161***		-0.042*	-0.106***		0.147***	0.138***
		(0.013)	(0.019)		(0.017)	(0.021)		(0.017)	(0.020)		(0.018)	(0.022)
$D(ConsumerDiscretionary)$		-0.036**	-0.031		-0.101***	-0.092***		-0.087***	-0.096***		0.102***	0.151***
		(0.013)	(0.018)		(0.018)	(0.021)		(0.017)	(0.021)		(0.019)	(0.022)
$D(HealthCare)$		0.357***	0.317***		0.297***	0.283***		0.277***	0.396***		0.395***	0.481***
		(0.022)	(0.041)		(0.022)	(0.030)		(0.019)	(0.024)		(0.021)	(0.026)
$D(InformationTechnology)$		0.078***	0.281***		-0.029	0.043		0.095***	0.224***		0.183***	0.297***
		(0.017)	(0.027)		(0.020)	(0.026)		(0.018)	(0.024)		(0.020)	(0.028)
RD/A	1.334***	1.102***	1.602***	0.597***	0.431***	0.455**	0.394***	0.290***	0.395***	0.395***	0.288***	0.634***
	(0.071)	(0.071)	(0.136)	(0.029)	(0.028)	(0.147)	(0.016)	(0.015)	(0.081)	(0.017)	(0.017)	(0.134)
interacted with												
Materials			0.047			0.562*			0.841***			0.650*
			(0.280)			(0.235)			(0.218)			(0.272)
Industrials			-0.029			0.286			0.816***			0.180
			(0.187)			(0.176)			(0.149)			(0.161)
Consumer Discretionary			-0.244			-0.098			0.310*			-0.320*
			(0.202)			(0.171)			(0.137)			(0.159)
Health Care			-0.272			-0.001			-0.170*			-0.384**
			(0.217)			(0.152)			(0.082)			(0.135)
Information Technology			-1.146***			-0.160			-0.212*			-0.448**
			(0.153)			(0.150)			(0.083)			(0.137)
PAT/RD	0.036***	0.033***	0.019	0.017**	0.018**	0.001	0.089***	0.105***	0.299***	0.109***	0.118***	0.377***
	(0.006)	(0.006)	(0.011)	(0.005)	(0.006)	(0.001)	(0.014)	(0.015)	(0.060)	(0.017)	(0.018)	(0.108)
interacted with												
Materials			0.017			0.040			-0.208**			-0.044
			(0.014)			(0.024)			(0.065)			(0.165)
Industrials			0.006			0.027**			-0.237***			-0.361***
			(0.015)			(0.009)			(0.061)			(0.108)
Consumer Discretionary			0.021			0.011*			-0.176*			-0.319**
			(0.019)			(0.005)			(0.074)			(0.110)
Health Care			0.060*			0.046*			-0.173*			-0.238*
			(0.027)			(0.021)			(0.071)			(0.112)
Information Technology			0.008			0.019			-0.189**			-0.290**
			(0.014)			(0.012)			(0.071)			(0.111)
$D(RD=0)$	0.077***	0.092***	0.127***	-0.070***	-0.050***	-0.022	-0.078***	-0.018	0.058***	-0.011	0.061***	0.097***
	(0.014)	(0.014)	(0.015)	(0.013)	(0.012)	(0.015)	(0.014)	(0.015)	(0.017)	(0.016)	(0.017)	(0.019)
#Firms	2095	2095	2095	2923	2923	2923	3605	3605	3605	2966	2966	2966
#Observations	12288	12288	12288	16440	16440	16440	22122	22122	22122	17564	17564	17564
R^2	0.242	0.274	0.288	0.234	0.274	0.280	0.264	0.285	0.305	0.265	0.284	0.298
Standard Error	0.503	0.493	0.488	0.618	0.602	0.599	0.713	0.702	0.693	0.698	0.690	0.683
Robust Wald Test for added												
effects (degrees of freedom)		74.26 (5)	9.52 (10)		127.91 (5)	4.91 (10)		117.15 (5)	11.41 (10)		79.78 (5)	9.34 (10)

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses. All equations include a complete set of year dummies.
The left-out category is *Others*.

RD/A. HJT also reports the same finding for 1979-1988, although their industry definition differs from ours.

Results with a full set of interaction terms are presented in columns, 3, 6, 9, and 12. We illustrate the findings in Figure 3, where the left (right) panel plots the trend in the coefficient of RD/A (PAT/RD) across sectors. Though in different degrees, the main trends largely appear in all.

Figure 3



The importance of R&D declined most notably in Consumer Discretionary, Health Care, and Others. R&D remains relatively more important in Materials and Industrials while the opposite is true for Information Technology. The variations are less heterogenous for the value of patents. The noteworthy developments occur in Others, whose coefficient for PAT/RD increased dramatically since the 1990s,[21] and Materials, for whom we observe a large rise in 2009-2017. Only in Industrials, patents have not become more valuable in the latest cohort compared to the 1980s.[22]

5. Young Firms

With excessive economic rents associated with patents, one might worry that the system provides incentives for patenting and not for inventiveness (e.g. Jaffe

[21] A component of Others potentially responsible for this observation is Telecommunication Services, in which there are 5, 24, 53, and 43 firms per each (chronologically ordered) cohort.

[22] One problem of fixed industry classification in our multi-cohort study is that firms themselves evolve. For example, IBM today is a very different company from its early days. The structure of US economy has also changed enormously.

and Lerner, 2004; Boldrin and Levine, 2008; Bessen and Meurer, 2008). To weigh in on this debate, we next examine whether the market values patents differentially for "young" firms.

The basic idea, borne out in the model of Klette and Kortum (2004) and others, is that young firms must be inventive to come into existence and to survive. At the same time, if patents were exploited not to protect new innovations but to protect existing market power, it would more likely be practiced by firms that have already built strong market positions.

To define firm age, we track the year in which each firm enters Compustat database. While Compustat records IPO dates, there are many inconsistencies and missing information.[23] Following Acemoglu *et al.* (2018), we define "young" firms as 0 to 9 years old and "mature" firms as 10 or more years of age.

Table 7 breaks down the number of observations associated with young firms in each cohort/industry. The share of such observations in each cohort is about one-third, except for 2009-2017. Consistent with Table 5, young firms appear most frequently in the Health Care and Information Technology sectors and during the 1990s and 2000s.

Table 7: Young Firms

	Cohort			
Industry Sector (GICS[1] Code)	**1979-1988**	**1989-1998**	**1999-2008**	**2009-2017**
Materials (15)	228	376	344	91
Industrials (20)	732	1012	812	320
Consumer Discretionary (25)	425	798	662	185
Health Care (35)	647	1963	2380	1550
Information Technology (45)	1262	2173	3151	775
Others (0,10,30,40,50,55,60)[2]	563	521	776	279
Total Young	3857	6843	8125	3200
Total All	12288	16440	22122	17564

[1] Global Industry Classification Standard
[2] 0=unassigned firms.

Table 8 presents the estimation results with young firm dummies. We fo-

[23] Other papers have also used the entry year, either in Compustat or Census, as the basis to proxy firm age (e.g. Hadlock and Pierce, 2010; Haltiwanger, Jarmin, and Miranda, 2013; Acemoglu *et al.*, 2018).

cus on the R&D and patent regressors. See Appendix B for the corresponding regression results over 5-year cohorts (Tables 13 and 14).

Table 8: Young Firm Effects

Variable	Cohort											
	1979-1988			1989-1998			1999-2008			2009-2017		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$D(Young)$		0.280***	0.138***		0.212***	0.205***		0.161***	0.178***		0.296***	0.262***
		(0.011)	(0.018)		(0.011)	(0.015)		(0.011)	(0.016)		(0.017)	(0.028)
RD/A	1.334***	1.005***	0.580***	0.597***	0.508***	0.488***	0.394***	0.367***	0.426***	0.395***	0.358***	0.353***
	(0.071)	(0.061)	(0.059)	(0.029)	(0.027)	(0.044)	(0.016)	(0.016)	(0.022)	(0.017)	(0.017)	(0.018)
$\times\ Young$			0.776***			0.038			-0.121***			0.017
			(0.099)			(0.050)			(0.029)			(0.041)
PAT/RD	0.036***	0.019***	-0.001	0.017**	0.009*	0.016*	0.089***	0.087***	0.039***	0.109***	0.097***	0.055***
	(0.006)	(0.005)	(0.002)	(0.005)	(0.004)	(0.007)	(0.014)	(0.013)	(0.009)	(0.017)	(0.016)	(0.014)
$\times\ Young$			0.039***			-0.008			0.133***			0.119**
			(0.009)			(0.008)			(0.031)			(0.040)
$D(RD=0)$	0.077***	0.040**	0.002	-0.070***	-0.074***	-0.073***	-0.078***	-0.072***	-0.068***	-0.011	-0.006	-0.014
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.016)	(0.015)	(0.015)
#Firms	2095	2095	2095	2923	2923	2923	3605	3605	3605	2966	2966	2966
#Observations	12288	12288	12288	16440	16440	16440	22122	22122	22122	17564	17564	17564
R^2	0.242	0.287	0.298	0.234	0.255	0.255	0.264	0.272	0.275	0.265	0.284	0.285
Standard Error	0.503	0.488	0.484	0.618	0.610	0.610	0.713	0.709	0.707	0.698	0.689	0.689
Robust Wald Test for added effects (degrees of freedom)		600.54 (1)	36.42 (2)		388.05 (1)	0.77 (2)		202.62 (1)	20.15 (2)		320.30 (1)	4.42 (2)

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.

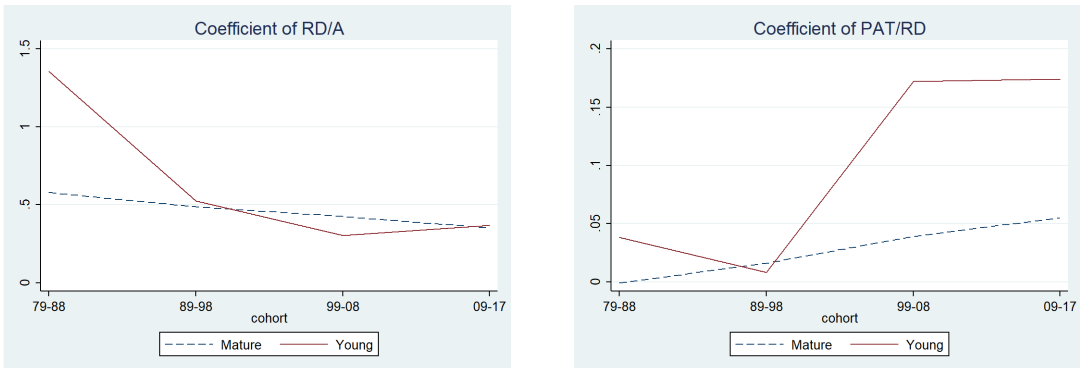
The young firm dummy is positive and statistically significant in all cohorts and every regression, consistent with these firms being indeed rewarded for novel innovations and greater profitability. The interaction terms reveal further interesting observations.

In the 1979-1988 cohort, the coefficients for interaction with both RD/A and PAT/RD are positive and statistically significant but these young firm effects disappear in the 1989-1998 cohort.

The most noteworthy observation is then found in the 1999-2008 cohort. Here, the coefficient for $RD/A \times Young$ is significantly negative while, for $PAT/RD \times Young$, the estimate is positive and significant. In particular, the value contribution of patent yield for young firms (equal to 0.172) is nearly twice the average effect (0.089) and more than four times the value to mature firms (0.039).

In the 2009-2017 cohort, young firms' patents continue to be more important for firm value than patents of the rest of sample firms. R&D contributes slightly more to firm value for young than mature firms but the difference is statistically insignificant.

Figure 4



The role of young firms behind the overall trends becomes crystalized if we plot the estimates of each value component separately. In both panels of Figure 4, we see that mature firms' trends are fairly linear, while sizable shifts occur for young firms.

For the latter group, the coefficient of RD/A fell from 1.356 in 1979-1988 to 0.526 in 1989-1998 and since then has roughly tracked mature firms. The young firm premium on patents disappeared during the 1989-1999 cohort, but then the coefficient of $PAT/RD \times Young$ made an enormous jump, from 0.008 to 0.172, in the 1999-2008 cohort and remained substantially ahead of mature firms in the 2009-2017 cohort.

The new results thus imply that our aggregate findings are driven in large part by young firms. In particular, while the market value of patents has risen steadily for mature firms, the effects have been much more pronounced for the young. If we think of these firms as innovators then the observed growth of patent value since the turn of the new millennium may well capture an arrival of novel and highly profitable inventions.[24]

[24]It is interesting to observe however that young firms' patent value declined in 1989-1998, despite a large number of them coming into existence (Table 7). See footnote 18 for a related comment.

6. Robustness Issues

Patent Stocks with Application Date Patents are typically granted several years after their application, and therefore, the application date is closer to the time of invention. However, a recent study by Kogan *et al.* (2017) finds that significant stock market responses to patents occur around their grant, and not application, dates.

Also, our results are robust to using application dates for the construction of patent stock. We re-run the regression reported in Table 2 with the alternative patent stocks and report the results in Appendix C. Note here that, due to the application-grant lag, patent stocks computed for the recent years are likely to be undervalued.

Alternative Measure of Tobin's Q In this paper, we have estimated Tobin's Q by the simplified method of Gompers, Ishii, and Metrick (2003). A more extensive estimate using Compustat data can be obtained via the procedures of Lindenberg and Ross (1981).

This estimate is based on recursive calculation of the replacement cost of capital from the reported physical capital and inventory information. As such, it relies on how one sets the depreciation rate. Another issue is that it extracts the book values of preferred stock and debt directly but Compustat sometimes report negative values of debt, resulting also in negative Tobin's Q.

In Appendix C, we present a detailed description of the procedure and the corresponding regression results that parallel Table 2, dropping observations with negative Tobin's Q estimates. The central messages of the paper remain intact.

7. Concluding Discussion

Patents became better legally protected and easier to acquire through a series of reforms since early 1980s. Patenting began to surge and the exponential growth continued well into the new millennium. US firms have also been spending increasing amounts of resources to obtain patents.

Our evidence reveals that these patenting and R&D choices are associated with increased market value of patents. Markets have been putting increasing weights on the success of investment in the form of patents relative to R&D itself. Citations have also become less important. Though in different degrees, the observed trends appear across industries.

The incentive for innovation, as captured by market valuation of patent rents, has magnified. According to our estimation, on average, an extra patent per million dollars of R&D boosts firm value by as much as 11% in 2009-2017 compared to just over 3% in 1979-1988. Consistent with the large gain in patent rents, US firms have piled up R&D spending. Could all these efforts have been simply about patenting with little relation to true innovation?

This paper further demonstrates that, except for the 1990s, the market has been consistently valuing patents of young firms more highly than those of established firms, and moreover, this tendency was particularly strong during the years of rapid growth in overall patent value. The latter implies that if young firms are innovators then it is the arrival of new, profitable technologies that has largely driven our observations. The current US patent system may not be perfect, but at least it seems to be providing an ample platform for entrants to build success.

The declining value of R&D *per se* raises another intriguing possibility. While it suggests diminishing returns to R&D, it is also consistent with firms patenting their innovations at a greater rate. Many firms choose to keep their technologies as trade secrets as well. If our finding does reflect a shift away from trade secrets to open patents, the society could be set for a gain because of the eventual spillover effects that trade secrets would not allow (see Kultti, Takalo, and Toikka (2007) for a related theory).[25]

We wrap up by discussing several avenues of future research. First, identifying the cause of our findings remains a major outstanding question. Have the reforms been responsible for the growth of patent rents?[26] External factors, such as globalization, may have also contributed to the rising value of US patents.[27]

Second, to evaluate patent policy, we focused on patent rents and paid limited attention to citations. It may be useful to decompose them into multi-

[25]There are however many barriers to such positive externalities, one of which is geographic distance. Recently, Kwon, Lee, Lee, and Oh (2018) find that localization of knowledge spillovers is on the rise.

[26]For review of early attempts at addressing this issue, see Jaffe (2000) and Gallini (2002), among others.

[27]In a recent paper, Kwon, Lee, and Lee (2017) compare the quality of patents across countries and present evidence of the US strengthening its position as global innovation leader.

ple categories, as done by HJT. Furthermore, since 2001, USPTO distinguishes examiner-added citations from applicant citations, and as noted by several authors (e.g. Alcácer, Gittelman, and Sampat, 2009), this may contain interesting information about corporate patenting strategies that merits investigation, especially with our newly constructed dataset.

Appendix

A. Data Construction

A.1 Sources

Our firm-level dataset is constructed from matching three sources of data.

- USPTO's assignee harmonization project provides a list of "assignee" names compiled for the period 1976-2015.[28] For years 2016 and 2017, we obtain assignee names directly from USPTO bulk data. There are total 347909 assignees with 5195042 patents granted to them.
- We consider all firms included in the Computat database over the period 1960-2017. There are 38554 firms with unique identifiers, or GVKEYs.
- The 2018 edition of LexisNexis Corporate Hierarchy database provides parent-subsidiary relationships.

A.2 Name Standardization

We apply our name standardization procedures below to the USPTO assignee and Compustat firm lists.

- Step 1: NBER PDP
  - We begin by applying the NBER PDP algorithm (written in STATA).
  - It first standardizes common abbreviations and corrects spelling mistakes, leaving a "`standard`" name per assignee or firm.
  - It then removes corporate designators, leaving an additional "`stem`" name per assignee or firm.
  - We further remove parentheses and their contents as they mostly contain locational or additional information unrelated to assignee/firm names.
- Step 2: Complementing NBER PDP

[28] File name: ASG_NAMES_UPRD_69_15NUMSORT.txt

  - Among top 0.1% popular tokens left in the `stem` names after Step 1, those included in Douglas Hanley's name standardization algorithm are further removed.[29]
  - These tokens are `TECH`, `OF`, `HLDGS`, `THE`, `DE`, `A`, `NEW`, `TRUST`, and `FD`.
  - This procedure affects 11% of assignee names (or 10% of patents) and 12% of firm names.

- Step 3: Endowing assignee IDs
  - Compustat firms already have designated GVKEYs.
  - For USPTO, each assignee is endowed with a 9-digit (preliminary) unique identifier based on its `standard` name.[30]

Our name standardization procedure improves upon both USPTO's harmonized assignee list and the assignee list provided by NBER PDP itself.

For example, in the USPTO list, ABB DAIMLER-BENZ TRANSPORTATION (TECHNOLOGY) GMBH and ABB DAIMLER-BENZ TRANSPORTATION (DEUTSCHLAND) GMBH are given separate IDs (750045 and 735341) but they are the same firm. Our procedure correctly identifies both as ABB DAIMLER BENZ TRANSPORTATION GMBH and assigns unique ID 002622000.

The NBER PDP list, which we did not use, assigns a "pdpass" to each assignee. To give an example of error here, the list wrongly treats SAB WABCO HLDGS BV (pdpass=11186885) and SAB WABCO BV (pdpass=12079610) separately. Our list assigns ID 253259000 to both cases under SAB WABCO BV.

Our name standardization nonetheless remains imperfect. Other than the algorithmic limitations, the USPTO harmonized list may itself contain errors. For example, some patents of TERA PAK DEV SA in the NBER PDP list are assigned to TENTENAL PHOTOWERK WALTER GRABIG in the USPTO list.

Since we do not work directly with USPTO bulk data for the entire sample period, we cannot know for sure which list contains error. However, by checking patent numbers, we verified that about 0.6% of NBER PDP IDs are matched to multiple USPTO IDs, while 3% of USPTO IDs are matched to multiple NBER PDP IDs.

---

[29] See https://github.com/iamlemec/patents.

[30] This is a non-trivial issue. For example, GENERAL ELECTRIC COMPANY and GENERAL ELECTRIC CO LTD are two distinct `standard` names whose `stem` names are the same. But, the two in fact represent separate entities.

A.3 Matching

We take the lists of assignee IDs and GVKEYs generated by the above name standardization process and match them according to the procedures below. Our matching framework is similar to that of Kogan, Papanikolaou, Seru, and Stoffman (2017) who match USPTO data with CRSP data up to 2010.

- Step 1: Employing the result of NBER PDP
  - We begin by considering patents granted between January 1976 and December 2006 that exist in the NBER PDP database and are matched to a GVKEY.
  - For these patents, each of which is now endowed also with our own assignee ID, we identify assignee IDs that are matched to *single* GVKEYs.[31]
  - We extend these one-to-one matches between assignee IDs and GVKEYs to patents outside of the NBER PDP database (for years 2007-2017).
  - There are total 4754 matched assignee IDs accounting for about 8.8% of all assigned patents over 1976-2017.[32]
- Step 2: Matching algorithm of NBER PDP
  - For assignee IDs without matched GVKEYs in Step 1, we apply the NBER PDP name matching algorithm via Python.[33]
  - Matching algorithm
    1. Find perfect matches of `standard` names.
    2. If no perfect match, then calculate scores between a random pair of `stem` names based on "word token frequency".
       Let X denote a USPTO assignee name and Y denote a Compustat firm name in terms of the *set* of included *tokens*.

[31] This process eliminates cases with ownership changes which are recorded and assigned multiple GVKEYs by NBER PDP.

[32] For further verification, the first letters of matched company names are compared across USPTO and Compustat. This generated 395 matches with inconsistencies. Manual check on a subset of these cases all gave identical entities however, with the inconsistency stemming from either change of official firm name, subsidiary match, or other minor spelling variations.

[33] The NBER PDP algorithm is written in Perl.

Let X_k and Y_k denote k-th element in X and Y, respectively.
Let $f(X_k)$, or $g(Y_k)$, denote the total number of times that X_k, or Y_k, appears in the entire universe of assignee names in the USPTO data, or firm names in the Compustat data, in our initial sample.
Then, define

$$w_{X_k} := \frac{100}{f(X_k)} \text{ and } w_{Y_k} := \frac{100}{g(Y_k)}.$$

Two notions of X-to-Y match "scores" are given below:

$$\begin{aligned} SC(X,Y) &:= \sum_{X \cap Y} w_{X_k} \\ RSC(X,Y) &:= \frac{\sum_{X \cap Y} w_{X_k}}{\sum_{X} w_{X_k}}. \end{aligned}$$

We can similarly define the Y-to-X scores $SC(Y,X)$ and $RSC(Y,X)$.
X is matched to Y according to the thresholds set by NBER PDP:

- if $SC(X,Y) > 110$ or $SC(X,Y) > 100$ & $RSC(X,Y) > 45$;[34]
- unless there are more than 5 Compustat firm names matched as above.

We conduct both X-to-Y and Y-to-X matching and select only the intersection of the matches.

– Result: 4132 perfect (`standard` name) matches and 446 score-based (`stem` name) matches.

• Step 3: Further clean-up

– Duplicated matches

- For 294 perfect matches and 13 score-based matches from Step 2, multiple GVKEYs are matched to a single assignee ID.
- We first consult the match results of NBER PDP and select single GVKEY whenever this was possible; otherwise, check manually.

[34]Since our dataset contains a larger number of assignees and firms, the thresholds represent more conservative criteria compared to NBER PDP.

    - 159 matches are dropped.

  – Harmonization

    - If a GVKEY matched to an assignee ID in Step 2 has another matched assignee ID in Step 1, the two IDs are harmonized.

  – Final result: 8920 assignee IDs are matched to single GVKEYs.

A.4 Subsidiaries

A firm's patent holding may not give the full extent of its corresponding intellectual capital. For instance, one assignee could be a subsidiary of another, in which case there could be a reason to treat them under one umbrella. Another issue is mergers and acquisitions.

NBER PDP inherits the database constructed by by Hall, Jaffe, and Trajtenberg (2001) who managed to match major operating subsidiaries to their parent firms as of 1989 (based on the *Who Owns Whom* directory). NBER PDP adds an ownership chain by identifying successive GVKEYs associated with changes of ownership but does not go as far as revising the mapping between parent and subsidiary firms.

We update the parent-subsidiary relationships using the current 2018 edition of the LexisNexis Corporate Hierarchy database which contains 379402 distinct companies. Each company in the list is identified within a tree structure by the level of relationship with its parent as well as its type. The company types are Affiliate, Branch, Corporate Office, Division Group, Headquarters, Holding, Joint Venture, Parent, Plant, Representative Office, Shell, Subsidiary, and Unit. Companies at the top of the tree are referred to as "ultimate" parents, of which there are 15889.

- Step 1: Name Standardization
  - We apply the name standardization procedures described in Section A.2 to the list of LexisNexis firm names.
- Step 2: Patent-Subsidiary-Parent-Compustat matching
  - We first match the "parent" companies (not just ultimate parents) in the LexisNexis list to Compustat firms via the NBER PDP matching algorithm. There are 6313 such matches.

- Of these matches, whenever multiple parent companies are found for a single GVKEY, we use *location information* for one-to-one matching.

  Specifically, we pick the parent whose state or city location is identical to that of the Compustat firm;[35] otherwise, the match is dropped, unless there is missing information and the one-to-one match is chosen randomly.
- There are further 159 cases in which multiple GVKEYs are matched to single parent companies. We manually check these matches for one-to-one matching.

– We select all the firms in the LexisNexis list whose parent companies, or who themselves, exist in Compustat.

– We then apply the NBER PDP matching algorithm to the selected LexisNexis firms and USPTO assignees unmatched in Section A.3. There are 6485 such matches.[36]

  - Of these matches, whenever multiple LexisNexis firms are found for a single patent assignee ID, we use location information for one-to-one matching as above.
  - There are further 20 cases in which multiple assignee IDs are matched to single LexisNexis firm. We manually check these matches for one-to-one matching.

– We finally map the "Assignee ID-Subsidiary-Parent-GVKEY" chain.

• Result

- We match 4634 additional assignee IDs and 287679 patents (about 5.5% of all assigned patents in the sample).
- Out of these 4634 matches, 2607 are of the "subsidiary" type and 1918 are "shell" companies; 14 are "parent" companies themselves, 3 of which are harmonized with the list of matched Compustat firms from Section A.3.

[35]There are spelling inconsistencies in city names, for which we invoke the Levenshtein distance (less than or equal to 2) and manual verification.

[36]One shortcoming of our parent-subsidiary revision is therefore the possibility of ownership changes that may have occurred among the previously matched assignees.

- Additional 597 Compustat firms are matched to assignee IDs; 11 are, as indicated above, firms specified by LexisNexis as parent themselves (i.e. companies that our previous matching failed to pick up); the remainder are firms for whom only subsidiaries engage in patenting.

A.5 Notes on Our Identifiers

We describe our identifiers which also contain some additional information.

- Assignee ID
  - 4 to 8-digit number
  - The last digit identifies its type, i.e. parent, subsidiary, shell, or others, where a parent refers also to all those matched in Section A.3.
  - The second last digit identifies whether it has been harmonized (about 2%).
  - Example
    - ID 32701 - subsidiary and not harmonized
    - ID 208610 - parent and harmonized
- Firm ID
  - 5 to 7-digit number based on GVKEY
  - The last digit identifies whether the firm is matched from LexisNexis in Section A.4
  - Example
    - ID 12830 - parent firm is patenting
    - ID 1329811 - parent firm is not patenting

B. Additional Results

Table 9: Market Value of Knowledge Stocks: 5-year Cohorts

	Cohort							
Variable	**1979-1983**	**1984-1988**	**1989-1993**	**1994-1998**	**1999-2003**	**2004-2008**	**2009-2013**	**2014-2017**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD/A	2.076***	1.165***	0.670***	0.543***	0.429***	0.355***	0.423***	0.458***
	(0.136)	(0.091)	(0.054)	(0.033)	(0.024)	(0.022)	(0.025)	(0.031)
PAT/RD	0.039***	0.066***	0.034**	0.010*	0.048**	0.138***	0.138***	0.100***
	(0.010)	(0.011)	(0.013)	(0.004)	(0.015)	(0.024)	(0.029)	(0.018)
$D(RD = 0)$	0.110***	0.115***	0.004	-0.138***	-0.169***	0.026	0.036	-0.070**
	(0.022)	(0.021)	(0.021)	(0.017)	(0.020)	(0.021)	(0.022)	(0.023)
#Firms	1469	1622	1764	2427	2868	2685	2371	2319
#Obervations	5629	5816	6601	8734	10558	10649	9311	7654
R^2	0.250	0.259	0.220	0.218	0.238	0.270	0.283	0.248
Standard Error	0.494	0.499	0.614	0.612	0.748	0.680	0.686	0.696

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.

Table 10: Market Value of Knowledge Stocks with Citations: 5-year Cohorts

Variable	Cohort											
	1979-1983		1984-1988		1989-1993		1994-1998		1999-2003		2004-2008	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RD/A	2.165***	1.785***	1.195***	1.047***	0.693***	0.581***	0.553***	0.446***	0.484***	0.400***	0.389***	0.348***
	(0.156)	(0.129)	(0.100)	(0.092)	(0.062)	(0.054)	(0.037)	(0.031)	(0.027)	(0.023)	(0.025)	(0.022)
PAT/RD	0.041***	0.037***	0.071***	0.068***	0.032*	0.033**	0.013*	0.011*	0.063***	0.057***	0.154***	0.147***
	(0.011)	(0.009)	(0.011)	(0.011)	(0.014)	(0.012)	(0.005)	(0.005)	(0.017)	(0.016)	(0.026)	(0.024)
$CITES/PAT$	0.049***		0.017***		0.019***		0.015***		0.009***		0.008***	
	(0.005)		(0.002)		(0.002)		(0.001)		(0.001)		(0.001)	
$D(RD=0)$	0.123***	0.096***	0.125***	0.116***	0.024	0.012	-0.094***	-0.108***	-0.127***	-0.136***	0.039	0.039
	(0.022)	(0.022)	(0.021)	(0.020)	(0.021)	(0.021)	(0.016)	(0.016)	(0.020)	(0.020)	(0.021)	(0.021)
Citation Dummies[1]												
$D1$[2]		-0.074***		-0.059***		-0.021		0.016		0.081***		0.014
		(0.018)		(0.016)		(0.019)		(0.016)		(0.019)		(0.018)
$D2$[3]		-0.046**		0.022		0.085***		0.114***		0.121***		0.103***
		(0.017)		(0.019)		(0.022)		(0.019)		(0.021)		(0.019)
$D3$[4]		0.130***		0.147***		0.194***		0.274***		0.248***		0.182***
		(0.022)		(0.023)		(0.025)		(0.022)		(0.023)		(0.019)
$D4$[5]		0.399***		0.220***		0.365***		0.471***		0.497***		0.435***
		(0.045)		(0.041)		(0.045)		(0.039)		(0.048)		(0.047)
#Firms	1469	1469	1622	1622	1764	1764	2427	2427	2868	2868	2685	2685
#Observations	5629	5629	5816	5816	6601	6601	8734	8734	10558	10558	10649	10649
R^2	0.283	0.286	0.272	0.278	0.246	0.241	0.256	0.251	0.261	0.257	0.290	0.288
Standard Error	0.483	0.482	0.494	0.493	0.604	0.606	0.598	0.600	0.737	0.739	0.671	0.672

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.
[1] Baseline group: 0-2 (1401 obs), 0-3 (1606 obs), 0-4 (1732 obs), 0-5 (2117 obs), 0-5 (2469 obs), 0-5 (2677 obs) for each cohort in order
[2] 3 (1144 obs), 4-5 (1589 obs), 5-7 (1719 obs), 6-10 (2620 obs), 6-10 (2952 obs), 6-10 (2873 obs) for each cohort in order
[3] 4-5 (1797 obs), 6-8 (1315 obs), 8-12 (1598 obs), 11-17 (1852 obs), 11-20 (2487 obs), 11-20 (2489 obs) for each cohort in order
[4] 6-10 (1013 obs), 9-17 (1016 obs), 13-27 (1214 obs), 18-44 (1705 obs), 21-61 (2124 obs), 21-62 (2083 obs) for each cohort in order
[5] $>$10 (274 obs), $>$17 (290 obs), $>$27 (338 obs), $>$44 (440 obs), $>$61 (526 obs), $>$62 (527 obs) for each cohort in order

Table 11: Semi-elasticities with Citations

	Cohort								
	1979-1988			**1989-1998**			**1999-2008**		
Evaluated at:	Mean	Median	Total	Mean	Median	Total	Mean	Median	Total
RD/A	0.26	0.10	0.10	1.43	0.17	0.12	1.85	0.23	0.07
PAT/RD	0.89	0.26	0.36	0.62	0.13	0.17	0.39	0.09	0.14
$CITES/PAT$	5.01	3.73	4.95	11.93	7.64	10.47	17.80	9.63	13.22
Semi-elasticities									
$\frac{\partial logQ}{\partial(RD/A)}$	0.909***	1.106***	1.075***	0.295***	0.499***	0.492***	0.220***	0.369***	0.380***
	(0.039)	(0.056)	(0.054)	(0.009)	(0.024)	(0.025)	(0.005)	(0.014)	(0.015)
$\frac{\partial logQ}{\partial(PAT/RD)}$	0.025***	0.031***	0.030***	0.009**	0.016**	0.015**	0.055***	0.092***	0.095***
	(0.004)	(0.005)	(0.005)	(0.003)	(0.005)	(0.005)	(0.007)	(0.013)	(0.013)
$\frac{\partial logQ}{\partial(CITES/PAT)}$	0.018***	0.022***	0.021***	0.008***	0.014***	0.013***	0.004***	0.007***	0.007***
	(0.001)	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)

Semi-elasticities are computed using the estimated coefficients in the first column of each cohort of Table 3.
Heteroskedastic-consistent standard errors are shown in parentheses.

Table 12: Industry Effects with Citations

Variable	Cohort								
	1979-1988			1989-1998			1999-2008		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
D($Materials$)		-0.052***	-0.029		-0.110***	-0.273***		-0.119***	-0.209***
		(0.014)	(0.030)		(0.018)	(0.033)		(0.019)	(0.028)
D($Industrials$)		0.032*	0.052		-0.097***	-0.265***		-0.016	-0.203***
		(0.013)	(0.029)		(0.017)	(0.029)		(0.017)	(0.025)
D($ConsumerDiscretionary$)		-0.027*	0.017		-0.092***	-0.184***		-0.085***	-0.202***
		(0.013)	(0.028)		(0.018)	(0.031)		(0.017)	(0.027)
D($HealthCare$)		0.321***	0.254***		0.246***	0.201***		0.262***	0.348***
		(0.022)	(0.052)		(0.022)	(0.038)		(0.019)	(0.028)
D($InformationTechnology$)		0.050**	0.293***		-0.099***	-0.200***		0.031	-0.015
		(0.017)	(0.036)		(0.020)	(0.034)		(0.017)	(0.029)
RD/A	1.388***	1.178***	1.638***	0.617***	0.484***	0.471**	0.437***	0.331***	0.393***
	(0.079)	(0.078)	(0.147)	(0.033)	(0.033)	(0.151)	(0.018)	(0.018)	(0.080)
interacted with									
Materials			0.116			0.644*			0.841***
			(0.300)			(0.253)			(0.218)
Industrials			0.011			0.307			0.896***
			(0.203)			(0.190)			(0.158)
Consumer Discretionary			-0.196			-0.063			0.264
			(0.215)			(0.180)			(0.147)
Health Care			-0.126			0.028			-0.157
			(0.248)			(0.157)			(0.082)
Information Technology			-1.158***			-0.125			-0.158
			(0.165)			(0.155)			(0.084)
PAT/RD	0.039***	0.035***	0.020	0.019**	0.019**	0.001	0.109***	0.117***	0.296***
	(0.007)	(0.006)	(0.012)	(0.006)	(0.006)	(0.002)	(0.016)	(0.016)	(0.060)
interacted with									
Materials			0.018			0.035			-0.204**
			(0.015)			(0.025)			(0.064)
Industrials			0.006			0.026**			-0.226***
			(0.016)			(0.009)			(0.061)
Consumer Discretionary			0.019			0.011*			-0.166*
			(0.020)			(0.005)			(0.076)
Health Care			0.068*			0.040*			-0.166*
			(0.030)			(0.020)			(0.072)
Information Technology			0.013			0.058**			-0.102
			(0.016)			(0.019)			(0.077)
$CITES/PAT$	0.027***	0.021***	0.029***	0.017***	0.014***	0.002	0.008***	0.007***	-0.000
	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
interacted with									
Materials			-0.012			0.013**			0.000
			(0.008)			(0.004)			(0.003)
Industrials			-0.010			0.019***			0.011***
			(0.008)			(0.003)			(0.002)
Consumer Discretionary			-0.014			0.013***			0.010***
			(0.008)			(0.004)			(0.002)
Health Care			-0.001			0.006**			0.003***
			(0.009)			(0.002)			(0.001)
Information Technology			-0.014*			0.018***			0.010***
			(0.007)			(0.002)			(0.001)
$D(RD=0)$	0.096***	0.105***	0.137***	-0.035**	-0.033**	-0.011	-0.050***	-0.012	0.057***
	(0.014)	(0.014)	(0.015)	(0.013)	(0.012)	(0.015)	(0.014)	(0.015)	(0.017)
#Firms	2095	2095	2095	2923	2923	2923	3605	3605	3605
#Observations	12288	12288	12288	16440	16440	16440	22122	22122	22122
R^2	0.261	0.286	0.299	0.266	0.298	0.307	0.283	0.301	0.322
Standard Error	0.497	0.489	0.484	0.605	0.592	0.588	0.703	0.695	0.684
Robust Wald Test for added effects (degrees of freedom)		59.26 (5)	6.31 (15)		108.00 (5)	8.35 (15)		97.78 (5)	14.04 (15)

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.
The left-out category is *Others*.

Table 13: Young Firm Effects: 5-year Cohorts (1)

Variable	Cohort											
	1979-1983			1984-1988			1989-1993			1993-1998		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$D(Young)$		0.328***	0.161***		0.231***	0.082**		0.262***	0.169***		0.179***	0.224***
		(0.017)	(0.026)		(0.016)	(0.027)		(0.017)	(0.026)		(0.014)	(0.019)
RD/A	2.076***	1.476***	0.798***	1.165***	0.920***	0.514***	0.670***	0.530***	0.287***	0.543***	0.467***	0.572***
	(0.136)	(0.108)	(0.084)	(0.091)	(0.083)	(0.095)	(0.054)	(0.049)	(0.074)	(0.033)	(0.032)	(0.063)
$\times$ $Young$			1.302***			0.699***			0.468***			-0.162*
			(0.181)			(0.137)			(0.092)			(0.067)
PAT/RD	0.039***	0.014	-0.007	0.066***	0.048***	0.021**	0.034**	0.013	0.063***	0.010*	0.006	0.003
	(0.010)	(0.007)	(0.005)	(0.011)	(0.009)	(0.008)	(0.013)	(0.009)	(0.019)	(0.004)	(0.004)	(0.008)
$\times$ $Young$			0.033**			0.058**			-0.054**			0.003
			(0.012)			(0.019)			(0.020)			(0.009)
$D(RD=0)$	0.110***	0.031	-0.010	0.115***	0.089***	0.047*	0.004	-0.016	-0.016	-0.138***	-0.140***	-0.132***
	(0.022)	(0.020)	(0.018)	(0.021)	(0.020)	(0.021)	(0.021)	(0.020)	(0.023)	(0.017)	(0.016)	(0.017)
#Firms	1469	1469	1469	1622	1622	1622	1764	1764	1764	2427	2427	2427
#Observation	5629	5629	5629	5816	5816	5816	6601	6601	6601	8734	8734	8734
R^2	0.250	0.313	0.327	0.259	0.290	0.301	0.220	0.251	0.262	0.218	0.234	0.235
Standard Error	0.494	0.473	0.468	0.499	0.488	0.485	0.614	0.601	0.597	0.612	0.607	0.606
Robust Wald Test for added												
effects (degrees of freedom)		377.33 (1)	28.01 (2)		205.35 (1)	15.94 (2)		226.84 (1)	18.29 (2)		152.98 (1)	3.16 (2)

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.

Table 14: Young Firm Effects: 5-year Cohorts (2)

Variable	Cohort											
	1999-2003			2004-2008			2009-2013			2014-2017		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$D(Young)$		0.141***	0.226***		0.137***	0.164***		0.290***	0.243***		0.268***	0.315***
		(0.015)	(0.021)		(0.017)	(0.026)		(0.024)	(0.038)		(0.024)	(0.043)
RD/A	0.429***	0.391***	0.604***	0.355***	0.339***	0.378***	0.423***	0.389***	0.376***	0.458***	0.395***	0.441***
	(0.024)	(0.023)	(0.042)	(0.022)	(0.022)	(0.030)	(0.025)	(0.024)	(0.025)	(0.031)	(0.030)	(0.035)
$\times$ $Young$			-0.311***			-0.102*			0.064			-0.140*
			(0.046)			(0.041)			(0.060)			(0.064)
PAT/RD	0.048**	0.049***	0.025*	0.138***	0.128***	0.077***	0.138***	0.125***	0.095***	0.100***	0.093***	0.062***
	(0.015)	(0.015)	(0.011)	(0.024)	(0.023)	(0.023)	(0.029)	(0.027)	(0.026)	(0.018)	(0.017)	(0.017)
$\times$ $Young$			0.087*			0.104*			0.082			0.116*
			(0.039)			(0.047)			(0.066)			(0.054)
$D(RD=0)$	-0.169***	-0.165***	-0.141***	0.026	0.029	0.028	0.036	0.028	0.023	-0.070**	-0.064**	-0.061**
	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.023)	(0.023)	(0.023)
#Firms	2868	2868	2868	2685	2685	2685	2371	2371	2371	2319	2319	2319
#Observation	10558	10558	10558	10649	10649	10649	9311	9311	9311	7654	7654	7654
R^2	0.238	0.244	0.251	0.270	0.276	0.279	0.283	0.300	0.300	0.248	0.266	0.269
Standard Error	0.748	0.745	0.741	0.680	0.678	0.677	0.686	0.678	0.678	0.696	0.688	0.687
Robust Wald Test for added												
effects (degrees of freedom)		84.60 (1)	25.89 (2)		65.15 (1)	6.85 (2)		149.20 (1)	1.13 (2)		120.29 (1)	5.94 (2)

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.

C. Robustness

Patent Stock with Application Date

Table 15: Market Value of R&D and Patent Stocks: Application Date

	Cohort			
Variable	**1979-1988**	**1989-1998**	**1999-2008**	**2009-2017**
	(1)	(2)	(3)	(4)
RD/A	1.502***	0.581***	0.415***	0.444***
	(0.073)	(0.026)	(0.016)	(0.019)
PAT/RD	0.070***	0.002	0.120***	0.133***
	(0.007)	(0.002)	(0.014)	(0.020)
$D(RD = 0)$	0.124***	-0.103***	-0.043**	-0.029
	(0.014)	(0.012)	(0.014)	(0.015)
#Firms	2244	3333	3940	2862
#Observations	13251	18236	25328	18112
R^2	0.267	0.227	0.252	0.276
Standard Error	0.526	0.629	0.744	0.709

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Alternative Measure of Tobin's Q

We compute the following formula, based on Lindenberg and Ross (1981) and Nicholas (2008):

- Market value (MV) is the sum of the following:
  - market value of common stock (Compustat item CSHO $\times$ PRCC_C);
  - book value of preferred stock (Compustat item PSTKL);
  - book value of debt (Compustat items DLC + DLTT).
- Replacement cost of capital is the sum of the following:
  - book value of total assets (Compustat item AT)
  - replacement cost (RC) of physical asset (K^{RC}) less book value (BV) of physical capital (K^{BV}, Compustat item PPENT).

    We recursively define

    $$K^{RC}_{i,t} = K^{RC}_{i,t-1} \times \left[\frac{1+l}{1+r}\right] + (K^{BV}_{i,t} - K^{BV}_{i,t-1}),$$

    where l is the inflation rate, fitted with BEA's GNP deflator, and r is the depreciation rate, fixed at 5% as in Nicholas (2008).
  - RC of inventories (I^{RC}) less BV of inventories (I^{BV}, Compustat item INVT).

    We define

    $$I^{RC}_{i,t} = I^{BV}_{i,t} \times \left[\frac{p_t}{p_{t-1}}\right],$$

    where p is the producer price index of all commodities from BEA.

We drop observations with negative estimates.[37] The first table below summarizes the correlations between the original and alternative measures; the second table presents the regression results, which correspond to Table 2 in the main text.

[37] In the four cohorts, respecitvely, 0, 11, 33, and 12 observations were dropped as a result.

Table 16: Correlation: Original vs. Alternative Tobin's Q

	Cohort			
	1979-1988	**1989-1998**	**1999-2008**	**2009-2017**
	(1)	(2)	(3)	(4)
Tobin's Q	0.16	0.73	0.37	0.48
Log(Tobin's Q)	0.90	0.92	0.92	0.92
#Observations[1]	11013	14104	20122	14734

[1] Number of observations with positive estimates in both samples.

Table 17: Market Value of R&D and Patent Stocks: Alternative Tobin's Q

	Cohort			
Variable	**1979-1988**	**1989-1998**	**1999-2008**	**2009-2017**
	(1)	(2)	(3)	(4)
RD/A	1.901***	0.788***	0.403***	0.370***
	(0.096)	(0.039)	(0.019)	(0.018)
PAT/RD	0.040***	0.029***	0.072***	0.084***
	(0.009)	(0.008)	(0.013)	(0.015)
$D(RD = 0)$	0.046*	-0.086***	-0.190***	-0.156***
	(0.019)	(0.017)	(0.015)	(0.017)
#Firms	1922	2544	3463	2750
#Observations	12025	15706	22285	17365
R^2	0.206	0.210	0.211	0.206
Standard Error	0.638	0.751	0.826	0.800

Estimation method: non-linear least squares.
Heteroskedastic-consistent standard errors are shown in parentheses.
All equations include a complete set of year dummies.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

References

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr (2018): "Innovation, Reallocation and Growth," forthcoming in *American Economic Review*.

Alcácer, J., M. Gittelman, and B. Sampat (2009): "Applicant and Examiner Citations in U.S. Patents: An Overview and Analysis," *Research Policy*, 38, 415-427.

Bessen, J. and M. J. Meurer (2008): *Patent Failure: How Judges, Bureaucrats, and Lawyers Put Innovators at Risk*. Princeton: Princeton University Press.

Bloom, N. and J. Van Reenen (2002): "Patents, Real Options and Firm Performance," *Economic Journal*, 112, C97-C116.

Boldrin, M. and D. K. Levine (2008): *Against Intellectual Monopoly*. Cambridge: Cambridge University Press.

Cockburn, I. M. and M. J. MacGarvie (2009): "Patents, Thickets and the Financing of Early-Stage Firms: Evidence from the Software Industry," *Journal of Economics & Management Strategy*, 18, 729-773.

Foster, L., J. Haltiwanger, and C. Syverson (2008): "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review*, 98, 394-425.

Gallini, N. T. (2002): "The Economics of Patents: Lessons from Recent U.S. Patent Reform," *Journal of Economic Perspectives*, 16, 131-154.

Gambardella, A., D. Harhoff, and B. Verspagen (2008): "The Value of European Patents," *European Management Review*, 5, 69-84.

Graham, S. J. H., R. P. Merges, P. Samuelson, and T. M. Sichelman (2009) "High Technology Entrepreneurs and the Patent System: Results of the 2008 Berkeley Patent Survey," *Berkeley Technology Law Journal*, 24, 255-327.

Greenberg, G. (2013): "Small Firms, Big Patents? Estimating Patent Value using Data on Israeli Start-ups' Financing Rounds," *European Management Review*, 10, 183-196.

Griliches, Z. (1981): "Market Value, R&D, and Patents," *Economic Letters*, 7, 183-187.

Griliches, Z. (1994): "Productivity, R&D, and the Data Constraint," *American Economic Review*, 84, 1-23.

Hadlock, C. J. and J. R. Pierce (2010): "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index," *Review of Financial Studies*, 23, 1909-1940.

Hall, B. H. (1990): "The Manufacturing Sector Master File: 1959-1987," Working Paper No. 3366, National Bureau of Economic Research.

Hall, B. H. (2000): "Innovation and Market Value," in *Productivity, Innovation and Economic Performance*, ed. by R. Barrell, G. Mason and M. O'Mahoney. Cambridge: Cambridge University Press, 188-198.

Hall, B. H. (2018): "Is There a Role for Patents in the Financing of New Innovative Firms?" forthcoming in *Industrial and Corporate Change*.

Hall, B. H., A. Jaffe, and M. Trajtenberg (2001): "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools," Working Paper No. 8498, National Bureau of Economic Research.

Hall, B. H., A. Jaffe, and M. Trajtenberg (2005): "Market Value and Patent Citations," *RAND Journal of Economics*, 36, 16-38.

Hall, B. H. and R. H. Ziedonis (2001): "The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995," *RAND Journal of Economics*, 32, 101-128.

Haltiwanger, J., R. S. Jarmin, and J. Miranda (2013): "Who Creates Jobs? Small versus Large versus Young," *Review of Economics and Statistics*, 95, 347-361.

Harhoff, D., F. Narin, F. M. Scherer, and K. Vopel (1999): "Citation Frequency and the Value of Patented Inventions," *Review of Economics and Statistics*, 81, 511-515.

Hsu, D. H. and R. H. Ziedonis (2013): "Resources as Dual Sources of Advantage: Implications for Valuing Entrepreneurial-firm Patents," *Strategic Management Journal*, 34, 761-781.

Jaffe, A. (2000): "The U.S. Patent System in Transition: Policy Innovation the Innovation Process," *Research Policy*, 29, 531-557.

Jaffe, A. and J. Lerner (2004): *Innovation and its Discontents: How Our Broken Patent System is Endangering Innovation and Progress, and What to Do About It.* Princeton: Princeton University Press.

Klette, T. J. and S. Kortum (2004): "Innovating Firms and Aggregate Innovation," *Journal of Political Economy*, 112, 986-1018.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman (2017): "Technological Innovation, Resource Allocation, and Growth," *Quarterly Journal of Economics*, 132, 665-712.

Kortum, S. and J. Lerner (1999): "What is Behind the Recent Surge in Patenting?" *Research Policy*, 28, 1-22.

Kultti, K., T. Takalo, and J. Toikka (2007): "Secrecy versus Patenting," *RAND Journal of Economics*, 38, 22-42.

Kwon, S., J. Lee, and S. Lee (2017): "International Trends in Technological Progress: Evidence from Patent Citations, 1980-2011," *Economic Journal*, 127, F50-F70.

Kwon, H-S., J. Lee, S. Lee, and R. Oh (2018): "Knowledge Spillovers and Patent Citations: Trends in Geographic Localization, 1976-2015," Working Paper, Seoul National University.

Lanjouw, J. O. and M. Schankerman (2004): "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators," *Economic Journal*, 114, 441-465.

Lerner, J. (1994): "Venture Capitalists and the Decision to Go Public," *Journal of Financial Economics*, 35, 293-316.

Lindenberg, E. B. and S. A. Ross (1981): “Tobin’s Q Ratio and Industrial Organization,” *Journal of Business*, 54, 1-32.

Nicholas, T. (2008): “Does Innovation Cause Stock Market Runups? Evidence from the Great Crash,” *American Economic Review*, 98, 1370-1396.

Pakes, A. and M. Schankerman (1984): “The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources,” in *R&D, Patents, and Productivity*, ed. by Z. Griliches. Chicago: University of Chicago Press, 73-88.

Shapiro, C. (2000): “Navigating the Patent Thicket: Cross Licenses, Patent Pools, and Standard Setting,” *Innovation Policy and the Economy*, 1, 119-150.