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Benchmarking U.S. university patent value and commercialization efforts: A new approach

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ABSTRACT

Despite the economic significance of patented university research, it is difficult to measure the economic value of academic patented inventions and observe the extent to which universities are able to capture such value through patent licensing. Moving beyond assessing commercialization performance by simple statistics, we propose a new approach to benchmarking university patents and commercialization performance based on comparative corporate patent value. Our procedure involves matching university patents to patents with similar patent characteristics granted to public corporations, then estimating the "potential value" of these university patents by stock market reactions to grants of the matched corporate patents. These estimated values of university patents can significantly explain the technology-level income from licensing by a leading US research university and the annual licensing income of the member universities of the Association of University Technology Managers' (AUTM). We find that AUTM universities realize an average of 16% of the estimated value of matched corporate patents. We also investigate correlates of university-level potential patent value and suggest avenues for future research.

1. Introduction

According to the Association of University Technology Managers' (AUTM) 2018 survey of U.S. university technology transfer operations, its 198 respondents filed over 17,000 patent applications and received about 7600 patent grants that year.[1] These patents based on university scientific research have generated significant income. For example, approximately $9.56 billion in licensing revenues accrued to participants of the AUTM survey over the 1991–2010 time period (our calculations based on AUTM data). In addition, in 2018 over 1000 new ventures were formed, and 828 new products based on university research were reported to have been introduced.

Recent examples of influential products based on scientific discoveries from university research include Emory University's HIV drug Emtricitabine, New York University's anti-inflammatory agent, Remicade (to treat rheumatoid arthritis), and the University of Pennsylvania's recent pioneering work in CAR-T immunotherapy. These advances have occurred not just in the life sciences; university-based breakthrough products have been achieved in cryptography (such as the RSA encryption algorithm), computing (autonomous vehicle technologies), and other fields.

Numerous assessments of economic activity based on university research have been generated based on the AUTM survey data (e.g., Huggett, 2017). These assessments and rankings are often based on simple statistics such as the number of patents granted, counts of startups formed or licensing revenues received. While informative, such approaches typically lack a comparative benchmark, making it difficult to gauge whether realized license revenues are "large" or "small".

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[1] While patenting by U.S. universities occurred as early as the 1920s, the 1980 Bayh–Dole Act (granting universities ownership of discoveries resulting from federally-funded research) is associated with a rise in university patenting, licensing, and commercialization efforts (Henderson et al., 1998; Mowery et al., 2004).

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Compounding the challenge of constructing a comparative benchmark is the issue of valuing intellectual property (IP). Even in the private sector context, estimating the economic value of patents or patent portfolios is notoriously difficult, as observable market transactions of patent sales or licenses are rare (the transfers do not occur regularly, and even when they do, transfers are privately negotiated and may be unrepresentative of the full distribution of patent values). Efforts to estimate the private value of corporate patents have been based on forward citations, corporate acquisition events, observed patent renewal fees at various stages of the patent lifecycle, or through patent disputes such as litigation.[2] All of these prior efforts at valuation are not contemporaneous to the patent grant event, and are only realized *ex post*. A further complication arises in valuing university patents, as there is a debate about the extent to which academic institutions should be involved in technology commercialization and economic development in addition to its traditional mission of teaching and research (e.g., Bok, 2003; Sanberg et al., 2014).

To address the challenge of contemporaneous and broader patent valuation, we base our patent value estimates using stock market reactions to patent grants (following Kogan et al., 2017). We estimate the notional "potential" economic value of university patents as benchmarked to a similar portfolio of patents granted to private firms, after controlling for the effect of private firms' complementary assets (such as marketing, production, and logistics). Interpreting such comparisons requires care, as they traverse social value creation and private value capture. We discuss this issue at length in our concluding section.

To fulfill their misson of public benefit, universities rely on a number of revenue sources including tuition income, endowment returns, philanthropy, and increasingly, commercialization revenues. These sources help further the traditional activities of the modern research university in the domains of teaching and research. Benchmarking IP asset valuation therefore directly impacts financial resources for the mainstream university mission in addition to the increasing call for university involvement in commercialization and economic development more generally (Sanberg et al., 2014).

2. Data, method & results

Our method follows a five-step process: construct university patent portfolios (step 1); relate patent characteristics to estimated value in corporate patents (step 2); relate patents of a major U.S. research university to estimated value (step 3); relate AUTM licensing income and start-up to the estimated value (step 4), and explore the correlates of estimated university patent value (step 5). Our discussion of data, variables, and method below mirrors these steps.

2.1. Construct university patent portfolios (step 1)

We first collect data on patents granted to U.S. universities from 1976 to 2010. Specifically, we manually construct a list of assignees and corresponding identifiers that are U.S. universities, institutes, and foundations. The National Bureau of Economic Research (NBER) patent assignee file (1976–2006) allows us to identify all assignees in the category of "U.S. University".[3] We use other sources to identify research institutes and other entities affiliated with these universities.[4] We also manually search possible names (universities, research institutes, and foundations) in other non-university categories in the NBER patent assignee file and extract related unique identifiers (known as "PDPASS" in the dataset). This process results in a list of 362 U.S. universities which received at least one patent in the sample period. We report the University-PDPASS pairs in Table 1 of an electronic appendix available online.

Based on the university-PDPASS pairs, we construct a dataset of U.S. university patents. We combine the patent and citation data from NBER (Hall et al., 2001), Patent Network Dataverse of Harvard University (Li et al., 2014), and USPTO PatentsView to construct a dataset that includes detailed information on each patent granted to U.S. universities from 1976 to 2010.[5] The resulting sample consists of 77,880 university-linked patents.

These data allow us to construct variables for the following patent characteristics commonly used in the prior literature on (university) patenting: (i) *Quality* is defined as the number of forward citations received by a patent within five years after its grant year (Trajtenberg, 1990; Sampat and Ziedonis, 2004; Hall et al., 2005);[6] (ii) *Generality* is defined as one minus the Herfindahl-Hirschman Index (HHI) of patent subcategory citations received from forward citing patents (Trajtenberg et al., 1997; Hall et al., 2001); (iii) *Originality* is defined as one minus the HHI of patent subcategory citations of the focal patent (Trajtenberg et al., 1997; Hall et al., 2001; Hirshleifer et al., 2018); (iv) *Basicness* is defined as the ratio of the number of references to prior non-patent documents divided by the total references in the focal patent, which reflects patent dependence on scientific and academic knowledge (Fleming and Sorenson, 2004);[7] (v) *Claims* denotes the number of claims of each granted patent, which defines the coverage and scope of a patent (Lerner, 1994); and (vi) *IntlFamily* is defined as an indicator if the patent belongs to an international patent family (Harhoff et al., 2003; Nagaoka et al., 2010).[8]

We report the descriptive statistics of these measures in Table 1, comparing university patents in our sample with patents assigned to U.S. public firms.[9] University patents receive more forward patent citations (5.55 vs. 4.97) on average, are more general (0.44 vs. 0.38), are more original (0.42 vs. 0.36), are more "basic" (0.47 vs. 0.11), contain more claims (20.39 vs. 16.31), and less likely to be affiliated with international families (0.49 vs. 0.57), compared to corporate patents.[10]

[2] For example, Trajtenberg (1990), Harhoff et al. (1999), and Hall et al. (2005) have documented a positive relation between forward citations and market value. Lanjouw (1998) and Schankerman (1998) examine the relation between patent value and patent renewal. Others such as Bhagat et al. (1994) and Lerner (1995), and have examined market reactions to firms' involvement in patent litigation.

[3] For example, Harvard University has several different names in this category, including "Harvard College", "Harvard President & Fellows of Harvard College", "Harvard Univ. Office of Tech Transfer".

[4] Some university patents are assigned to categories other than universities, such as institutes (e.g., university hospitals) or research corporations affiliated to universities. We use the *U.S. News National University Rankings* and *Top 100 Worldwide Universities Granted U.S. Utility Patents* published by the National Academy of Inventors to help identify universities and their affiliates in our sample.

[5] The NBER database is available for download at http://www.nber.org/patents/; Patent Network Dataverse of Harvard University: https://dataverse.harvard.edu/dataverse/patent; and the USPTO PatentsView database: http://www.patentsview.org/web/.

[6] Lanjouw and Schankerman (2004) find that forward citations explain 48% of the variation of their patent quality index. Harhoff et al. (1999) and Hall et al. (2005) show that forward citations are associated with higher patent valuation from survey and stock price data, respectively.

[7] This variable is similar to the "Science" measure of Trajtenberg et al. (1997).

[8] We thank an anonymous reviewer for the suggestion of incorporating the effects of international patent family. We collected these data from the PATSTAT database.

[9] Our corporate patents include 1,361,771 patents granted to assignees in U.S. public firms (i.e., assignees with GVKEY identifiers) in the NBER assignee file from 1976-2010.

[10] Consistent patterns are observed in different sample periods (Panel A in the online Appendix Table 2), in distribution (Panel B in the online Appendix Table 2), and in different technology subcategories (Panel D to Panel I in the online Appendix Table 2). We also observe that university patents are concentrated in certain technology fields such as Drugs, Chemicals, and Surgery and Medical Instruments, as shown in Panel C of the online Appendix Table 2.

Table 1

Summary Statistics of Characteristics of Patents Granted to Public Firms and Universities in the U.S. We compare the distribution of patent quality (the citations received five years after the patent is granted), patent generality (one minus the Herfindahl-Hirschman Index (HHI) of citations received from other patents over patent subcategories), patent originality (one minus the HHI of citations given to other patents over patent subcategories), patent basicness (the ratio of the number of references to prior "non-patent documents" divided by the total references), number of claims, and international family (a dummy equals one if a patent belongs to an international family) of patents granted to public firms and universities. The definitions of generality, originality, and basicness follow Trajtenberg et al. (1997). ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively, when comparing the mean characteristics of universities' patents with those of public firms' patents. Sample period: 1976–2010.

	Universities						Public Firms					
	Quality	Generality	Originality	Basicness	Claims	Intl Family	Quality	Generality	Originality	Basicness	Claims	Intl Family
Mean	5.55***	0.44***	0.42***	0.47***	20.39***	0.49***	4.97	0.38	0.36	0.11	16.31	0.57
Median	2.00	0.50	0.49	0.50	17.00	0.00	2.00	0.40	0.36	0.00	14.00	1.00
Std. Dev.	10.31	0.32	0.34	0.35	17.34	0.50	9.06	0.32	0.33	0.20	13.03	0.49
Min.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
1st Pctl.	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
5th Pctl.	0.00	0.00	0.00	0.00	3.00	0.00	0.00	0.00	0.00	0.00	3.00	0.00
25th Pctl.	0.00	0.00	0.00	0.12	9.00	0.00	1.00	0.00	0.00	0.00	8.00	0.00
75th Pctl.	6.00	0.69	0.69	0.79	26.00	1.00	6.00	0.66	0.66	0.14	21.00	1.00
95th Pctl.	22.00	1.00	1.00	1.00	51.00	1.00	19.00	0.92	0.91	0.56	39.00	1.00
99th Pctl.	50.00	1.00	1.00	1.00	84.00	1.00	43.00	1.00	1.00	0.89	63.00	1.00
Max.	213.00	1.00	1.00	1.00	642.00	1.00	539.00	1.00	1.00	1.00	868.00	1.00
#Obs	77,880	77,880	77,880	77,880	77,880	77,880	1,361,771	1,361,771	1,361,771	1,361,771	1,361,771	1,361,771

These differences are all statistically significant, largely consistent with the literature (e.g., Trajtenberg et al., 1997; Henderson et al., 1998), and suggest high university patent commercial potential.

2.2. Relate patent characteristics to financial valuation in corporate patents (step 2)

We collect the patent value of corporate patents (i.e., patents assigned to public firms) from Kogan et al. (2017).[11] They calculate the value of a patent granted to a U.S. public firm using stock market reaction to the announcement of the patent grant. We proxy a public firm's patent value with the 3-day appreciation of market capitalization of this firm around the grant date of a patent, adjusted for measurement noise and various fixed effects. The details of the estimation are provided in the online Appendix (Section 1). The estimated patent value is also inflation-adjusted based on the consumer price index, CPI (the index is normalized as 1 for years 1982–1984).[12]

The estimated value of corporate patents results from both technological merit as well as corporate complementary assets such as marketing and production. We seek to disaggregate these two effects since universities do not possess the latter asset category. We regress the natural logarithm of one plus each corporate patent value (in millions) on its patent characteristics (*Quality, Generality, Originality, Basicness, Claims*, and *IntlFamily*) as well as the following firm characteristics of its assignee:[13] *R&D Intensity, Investment Intensity, SG&A Intensity, Ads Intensity*, and *M/B*. We also include the subcategory-year joint fixed effects to control for time-varying specific trends of different technology subcategories. Table 2 shows that patent quality, generality, basicness, and international patent family affiliation are positively associated with estimated patent value based on 450,329 patents granted to U.S.-listed firms.

2.3. Relate patents of a major U.S. research university to financial value (step 3)

In this step, we use the coefficients on patent characteristics estimated from step 2 to "fit/extrapolate" the value for university patents.[14] To assess this estimated value for university patents, we first make use of the complete patent licensing records of a major U.S. research university (step 3a) and then examine the extent to which the estimated university patent value explains licensing income (step 3b).

2.3.1. Licensing records from a major U.S. research university (step 3a)

The dataset includes 7,797 unique technologies and 779 licensing contracts from 1974 to 2018. Among unique technologies, 2,246 are licensed and 5,551 remain unlicensed. Not all technologies in the sample are patented. A licensing contract (i.e., agreement) includes one or more technologies with related patent numbers (if associated patent applications were filed and granted), licensing status, execution date, license fee, maximum royalty rate, exclusivity in licensing or not, lifetime revenue, technology fields, etc. There are on average 2.88 technologies included in a licensing contract. Among the 779 licensing contracts, 227 are exclusive, 12 are co-exclusive, and 540 are non-exclusive. The licensing revenue reflects the total amount of cash received based on licensing, royalties, or equity.[15] According to our interview with the university technology transfer director, the majority of licenses with startups do *not* include an equity component at this university; thus, lifetime revenue accrues primarily from license fees and royalties.

[11] The patent value data is downloadable via: https://iu.app.box.com/v/patents.

[12] Under the efficient market hypothesis, the stock market should reflect the value change due to patent grants in real time. Kogan et al.'s (2017) market reaction-based valuation approach follows Austin (1993) and is consistent with the valuation of patent litigation of Bhagat et al. (1994), Lerner (1995), and Bessen and Meurer (2012) and the valuation of new products of Chen et al. (2005). The method of Kogan et al. (2017) has been adopted in several subsequent studies including Almeida et al. (2019). An alternative way of evaluating the value of corporate patents is to collect the disclosed licensing contracts by public firms (see Kankanhalli et al., 2019); however, even those disclosed contracts are subject to selection issues and redactions.

[13] *R&D intensity* is the ratio of R&D expenditure over total assets to account for innovation input, *Investment intensity* is the ratio of capital expenditure over total assets to account for physical investment input, *SG&A intensity* is the ratio of selling, general & administrative expense over total assets to account for general human capital input, *Ads intensity* is the ratio of advertisement expenses

(*footnote continued*)
over total assets to account for marketing input, and *M/B* is the ratio of market equity over book equity to account for the growth opportunities perceived by the stock market.

[14] For each university patent, we estimate its patent value by multiplying its patent characteristics by coeffcients from Table 2, model (2).

[15] Note that all revenue income recorded at this level is inclusive of the amount which will be shared with the inventor and the inventor's department (which together represent an average of about 30% of the gross licensing revenues at this institution).

Table 2
Patent Characteristics and Corporate Patent Value. OLS regressions estimating the relation between patent and firm characteristics and patent value are reported. Excluding observations of missing corporate characteristics, our sample contains 450,329 patents of U.S.-listed firms. The dependent variable is the natural logarithm of one plus the patent value estimated by Kogan et al. (2017). The independent variables include six patent characteristics in natural logarithm (*Quality, Generality, Originality, Basicness, Claims*, and *IntlFamily* dummy), and five firm characteristics related to complementary assets in natural logarithm (*R&D Intensity, Investment Intensity, SG&A Intensity, Ads Intensity*, and *M/B*). *R&D Intensity* is the ratio of R&D expenditure over total assets. *Investment Intensity* is the ratio of capital expenditure over total assets. *SG&A Intensity* is the ratio of SG&A expenses over total assets. *Ads Intensity* is the ratio of advertisement expenses over total assets. *M/B* is the ratio of market equity over book equity. We also include the subcategory-year joint fixed effects to control for time-varying specific trends in different technology subcategories. Patent value is in $ millions and adjusted for inflation. All variables are winsorized at their 1% and 99% percentiles. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	(1) Not controlling for complementary assets	(2) Controlling for complementary assets
Quality	0.0477***	0.0423***
	(0.0016)	(0.0015)
Generality	0.0374***	0.0416***
	(0.0063)	(0.0058)
Originality	−0.0216***	−0.0210***
	(0.0060)	(0.0055)
Basicness	0.3232***	0.3110***
	(0.0092)	(0.0084)
Claims	0.0120***	0.0399***
	(0.0020)	(0.0019)
IntlFamily	−0.0005	0.0232***
	(0.0039)	(0.0036)
R&D Intensity	—	2.8461***
	—	(0.0427)
Investment Intensity	—	−1.4698***
	—	(0.0405)
SG&A Intensity	—	−3.9931***
	—	(0.0207)
Ads Intensity	—	8.4344***
	—	(0.0593)
M/B	—	0.7628***
	—	(0.0031)
Observations	450,329	450,329
R-squared	0.2740	0.3968
SubCat-Year FE	YES	YES

We focus on 765 licensed patents and 821 unlicensed patents from 1976 to 2010 and calculate a patent's licensing revenue as the lifetime revenue of the contract divided by the number of patents involved.[16] Because patents in our data have different "lifetimes" to be licensed, truncation bias is a potential concern and may thus underestimate the lifetime revenue.[17] Our dataset also includes unlicensed patents; their licensing revenue is assumed to be zero if the patent is never observed to generate positive revenue.[18] We discuss the summary statistics of the licensed and unlicensed patents in the online Appendix Table 3.

2.3.2. Relate university patents to financial value through patent characteristics (step 3b)

We now cross-check our valuation method by comparing the estimated patent values to patent licensing revenue in the 1,586 patents (765 licensed patents and 821 unlicensed patents) of a major U.S. research university. In particular, we regress the natural logarithm of one plus the patent lifetime revenue on the natural logarithm of one plus the estimated patent value (*PatVal*), controlling for other patent and contract characteristics, the joint fixed effects for technology field (by subcategory defined in Hall et al. (2001)) and year. As shown in Table 3, our estimated patent value is significantly and positively associated with the actual realized licensing revenue in all specifications. The fact that our estimated patent value explains realized licensing revenue suggests that our method indeed captures variation in university patent values. Taking Column (3) as an example, the coefficient on *PatVal* is 0.288, which implies that a patent worth $1 million is associated with $0.288 million of licensing income on average. As a result, Table 3 suggests that the focal university realizes approximately 21.5–28.8% of the total private value of corporate patents with similar patent characteristics.

2.4. Relate AUTM licensing income and start-up to financial value (step 4)

Similar to step 3, we use the coefficients on patent characteristics estimated from step 2 to "fit/extrapolate" the value for university patents for all universities in the AUTM record. We use a sample of 167 AUTM-member universities reporting the annual university-level license income and the number of startups formed from the AUTM annual reports from 1991 to 2010.[19] To understand to what extent a university's estimated patent value explains its total license income (and start-up) spanning multiple years, we estimate a cross-sectional regression that regresses universities' time-series average of annual license income on the time-series average of estimated patent value, *Average PatVal Capital*.[20] We report the regression estimations in both a linear form and a log form in Table 4 Panel A. We find that the coefficients on *Average PatVal Capital* are significant in all specifications, suggesting that the estimated patent value explains university-level license income. Taking Column (1) as an example, the coefficient on *Average PatVal Capital* is 0.156. This implies that an increase of $1 million worth in a university's new patents correlates with an increase of $0.16 million worth in a license income stream on average. This estimate suggests that AUTM universities realize 16% of the estimated value based on publicly-held corporate patents with similar patent characteristics as those from our sample of universities.

In Table 4 Panel B, we examine the relationship between our estimated university patent value and the number of startups formed at the university level. Similar to the approach used in Panel A, the time-series average of the number of startups created by the university is the

[16] Note that one patent may belong to two or more different licensing contracts. We treat these cases as different patents due to different contract condtions.

[17] For example, the lifetime revenue from a patent that was recently granted could be zero if it has not been licensed or may be underestimated as we can only observe its income until 2017. We take a conservative approach and do not extrapolate or estimate the future income from those patents that are subject to such truncation bias.

[18] This assumption may unavoidably underestimate the value of university patents for several reasons: (1) some unlicensed patents may have industrial value but remain unlicensed; and (2) patents may have been exploited by firms without the university receiving royalties if the university was not agressive in enforcing its IP rights.

[19] We use the CPI to adjust all annual licensing incomes to the level of 1982-1984. In this sample, the average, median, and standard deviation of annual license income (in millions) are 4.50, 0.69, and 16.75, respectively. Moreover, the average, median, and standard deviation of the number of startups formed are 2.84, 1.00, and 4.51, respectively.

[20] First, we define a university's patent value in year *t* as the sum of estimated values of all patents granted to the university in year *t*. The average, median, and standard deviation of estimated university patent value (in millions) are 10.74, 4.89, and 19.34, respectively. We then calculate the time-series average of each university's patent value to be the main explanatory variable, *Average PatVal Capital*, in Table 4. Each university-year observation is included in our regression sample for Table 4 when the university appears in the AUTM report in that year. In the 2,109 observations of university-year observations, we impose the missing license income of 36 observations (or 1.71% of the sample) to be zero.

Table 3

Patent Innovation Value and Actual University Patent Revenue. OLS regressions examining the explanatory power of estimated patent innovation value for realized patent revenue are reported. Our sample of patent revenue, including 765 licensed and 821 unlicensed patents, is obtained from a large patent office in a prominent U.S. university. The dependent variable is the natural logarithm of one plus the patent lifetime revenue. Lifetime revenue is split evenly to each intellectual property item in the same licensed agreement. If a patent is not licensed, we set its lifetime revenue as zero. Lifetime revenue and estimated patent value are in $ millions and adjusted for inflation. The independent variable of interest is the natural logarithm of one plus the estimated patent value (*PatVal*). To calculate *PatVal*, we first adopt regression model (2) in Table 2 and estimate the coefficients on patent characteristics. We then input the coefficient estimates and patent characterstics of each university patent and compute its *PatVal. PatVal* is set to be zero if it is estimated as negative. We also control for patent characteristics, such as patent quality, generality, originality, basicness, number of claims, international familty, patent sub-category by grant year fixed effects, and license agreement characteristics, such as a dummy indicating whether the patent is licensed or not and a dummy indicating whether the agreement is exclusive or not. All variables are winsorized at their 1% and 99% percentiles. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)
PatVal	0.2147***	0.4648***	0.2883**
	(0.0453)	(0.1564)	(0.1466)
Quality	—	−0.0007	−0.0008
	—	(0.0010)	(0.0009)
Generality	—	−0.0035	−0.0120
	—	(0.0155)	(0.0144)
Originality	—	−0.0283**	−0.0286**
	—	(0.0129)	(0.0120)
Basicness	—	−0.0823**	−0.0569*
	—	(0.0353)	(0.0331)
Claims	—	−0.0009*	−0.0007
	—	(0.0005)	(0.0005)
IntlFamily	—	0.0341***	0.0226***
	—	(0.0085)	(0.0080)
Licensed Dummy	—	—	0.0360***
	—	—	(0.0093)
Exclusivity	—	—	0.0911***
	—	—	(0.0094)
Observations	1,586	1,586	1,586
R-squared	0.2479	0.2729	0.3740
F statistics	22.43***	9.10***	29.35***
SubCat-Year FE	YES	YES	YES

dependent variable.[21] Results reported in Panel B are also based on cross-sectional regressions, in which we regress the time-series average number of startups created by a university on the university's *Average PatVal Capital*. Results suggest a positive and statistically significant relation and confirm the intuition that more technologically capable universities create more new businesses. In terms of economic magnitude, Column (1) suggests that three ($=0.1496\times19.34$) more startups will be formed in a year if the value of a university's patent portfolio increases by one standard deviation. Such an estimate is substantial given that sample average and median are 2.84 and 1.00, respectively, per year.

2.5. Explore the correlates of university patent value (step 5)

Finally, we discuss the university characteristics and inputs that correlate with patent value creation. After demonstrating that university patent value is correlated with both patent licensing and startup formation, we estimate a production function of university patent value

[21] Each university-year observation is included in our regression sample for Table 4 when the university appears in the AUTM report in that year. We assume that a missing value for startups in the report corresponds to a zero value (this occurs in 709 of the 2,109 total university-year observations).

Table 4

Association between Estimated Patent Value and License Income & Startups Formed across U.S. Universities. In this table, we examine the explanatory power of our estimated university patent value (*Average PatVal Capital*) for license income and number of startups formed at the university level. To do so, we run cross-sectional regressions of future license income (in Panel A) and future number of startups formed (in Panel B) on the capital of patent value. We define a university's capital patent value in year *t* as the sum of estimated values of all patents granted to the university in year *t*. We calculate the time-series average of each university's patent value to be the main explanatory variable, *Average PatVal Capital*. We then calculate the time-series average of each university's annual license income to be the dependent variable. Last, we regress universities' average total license income on *Average PatVal Capital* in Panel A. In Panel B, we use a similar approach to calculate the total number of startups per year. License income and patent value are in $ millions and adjusted for inflation. The data of license income and number of startups formed are from the annual reports of the Association of University Technology Managers (AUTM) 1991–2010. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Total License Income		
	(1)	(2)
Average PatVal Capital	0.1563***	0.5349***
	(0.0159)	(0.0391)
Constant	0.3359	−0.3189***
	(0.2746)	(0.0740)
Observations	167	167
R-squared	0.3694	0.6508
Specification	Linear-Linear	Log-Log
Panel B: Startups Formation		
	(1)	(2)
Average PatVal Capital	0.1496***	0.5059***
	(0.0074)	(0.0273)
Constant	0.9672***	0.1291**
	(0.1275)	(0.0518)
Observations	167	167
R-squared	0.7136	0.6750
Specification	Linear-Linear	Log-Log

to understand what inputs are crucial to valuable university patents. We collect several university variables as "inputs".[22] The first set includes five basic university characteristic variables including the five-year cumulative inflation-adjusted R&D expenditure (*R&D*, with a 20% obsolescence rate per year), the number of full-time faculty members (*Faculty*), a dummy variable indicating whether the sample university is a Carnegie-ranked research university or not (*Carnegie*), the full-time equivalents (*FTE*) in technology transfer office in that year, and a dummy variable indicating whether the sample university has a technology transfer office in that year (*TTO*). We also consider six additional university characteristics, including five-year cumulative NSF grants (*NSF*, with a 20% obsolescence rate per year), five-year cumulative NIH grants (*NIH*, with a 20% obsolescence rate per year), age of a sample university (*Age*), a dummy variable indicating whether the sample university has a medical school or not (*MedicalSchool*), a dummy variable indicating whether the sample university has a business school or not (*BusinessSchool*), and a dummy variable indicating whether the sample university is a member of the Ivy League or not (*IvyLeague*).[23]

[22] These input variables are considered because they are publicly available and have been discussed in Siegel and Wright (2015).

[23] *PatentVal, R&D, NSF*, and *NIH* are in $ millions and adjusted for inflation. *R&D* and *FTE* come from the annual reports of the Association of University Technology Managers (AUTM) 1991-2010. *Faculty, NSF*, and *NIH* are collected from the Carnegie reports (1994, 2000, 2005, and 2010). We assign the number of faculty members in 1994 to all years before 1994, and apply this rule to estimate the number of faculty for each university in all other years. All other variables are collected from online searches.

Table 5, Panel A reports the cross-sectional correlation matrix of these university characteristics. Not surprisingly, some variables are highly correlated. For example, the correlation coefficient between R&D expenditure and the number of full-time faculty (number of full-time equivalents) is 0.89 (0.92).

We then regress the estimated potential value of all patents applied by (and later granted to) a university in a year on several university characteristics in a log-log form assuming a Cobb-Douglas production function of patent value.[24] As in Table 4, we implement cross-sectional estimation by OLS regressions of the time-series average of university patent value on the time-series averages of all input variables. To avoid multi-collinearity, we first include these characteristics in regressions one-by-one in Columns (1) to (11) in Panel B. We find that almost all (except the business school dummy) are positively and significantly correlated with the output of patent value. When we include the five basic university characteristic variables together in one regression, we find that only R&D expenditure, the number of full-time faculty members, and the number of full-time equivalents in the TTO are statistically significant in Column (12). In terms of economic magnitude, a doubling of R&D expenditure, the number of full-time faculty, and TTO employees, is associated with patent value increases of 50%, 24%, and 37%, respectively, holding other variables fixed. The coefficients on *Carnegie, TTO,* and *Medical School* become insignificantly negative in Column (12), likely due to multi-collinearity. When we include all variables together in Column (19), we find that Ivy League affiliation also positively explains patent value output.

3. Discussion and conclusion

The degree to which universities should be in the business of commercially translating their scientific discoveries through patenting, licensing and startup efforts has long been, and continues to be, debated (e.g., Etzkowitz, 1994; Bok, 2003; Mowery et al., 2004; Siegel and Wright, 2015). These debates have often occurred with universities under budget constraints and pressures to justify their contributions to local communities and economies. Against this backdrop, our methodology sets a benchmark to estimate economic values associated with university patenting, thus offering a tool to administrators of universities a way to benchmark their commercialization efforts. In this section we interpret our results, discuss implications and limitations, and offer directions for future research.

The seminal "profiting from innovation" framework by Teece (1986) investigates conditions associated with imperfect organizational value capture, and provides insights that can put our results in perspective. Fig. 1 depicts a stylized relationship between economic value generation and its "capture." Panel A in this figure plots private value creation (x-axis) versus private value capture (y-axis). A 45-degree line from the origin represents complete capture of the value generated by the innovator (under perfect appropriability and control of organizational complementary assets). Departures from this condition (according to Teece, 1986) result in imperfect value capture by the innovator (represented by the dotted line below the 45-degree line).

Panel A of Fig. 1 represents the estimation we undertake: private economic value capture on the vertical axis and private economic value creation on the horizontal axis. We accomplish this by asking the counterfactual question: what would be the degree of value capture if private organizations held a similar patent portfolio as U.S. research universities? Universities, however, do not possess the downstream organizational complementary assets Teece identifies, such as sales, marketing and distribution capabilities necessary for commercialization. This difference between corporate organizations and universities is one important reason for diminished value capture by universities (our analysis in Table 2 aims to adjust for these differences). A second reason for a shallower value capture slope in Panel A is due to potential frictions in the market for technology transfer (again, stemming from the fact that universities are typically not self-commercializers, with the exception of startup venture creation for some universities). Such frictions stem from: (1) asymmetric information—sellers of technology, universities, may possess more information than the buyers (potential licensees) about the technology and the circumstances under which it works well, for example, and (2) the "embryonic" nature of many university discoveries, which requires further elaboration and proof of commercial development (Jensen and Thursby, 2001; Elfenbein, 2007; Ziedonis, 2007). As a result, the fraction of estimated economic value captured by university licensing revenues represents the proportion of the total value that is generated from "upstream" research by the university which may be dampened both by universities' lack of complementary assets for commercialization as well as the need to transfer the IP to commercializers.

This narrow interpretation of private economic value generation and capture neglects an important caveat. The missions of research universities within the U.S. have traditionally included numerous social goals including teaching, the wide dissemination of research results, and local economic development for the public good (Rosenberg and Nelson, 1994). As a result, our analysis underestimates value creation from commercializing university discoveries by an unknown extent. Panel B represents a more accurate picture of value capture in our university setting - *social* economic value capture versus *social* economic value creation. Similar to Panel A, the university captures a fraction of the societal value it generates (depicted by the dotted line in Panel B).

Estimates of social value creation and capture would require the inclusion of economic spillovers created from academic research activities in enhancing the human and knowledge capital of faculty members, lab researchers, and students, all of which are positively associated with future economic payoff (represented by the middle line in Panel B of Fig. 1). Measuring the value of such spillovers is challenging, however, even if they were narrowly construed, such as those associated solely with the commercialization process. Such analyses would require judgments regarding time horizon and would necessitate valuing difficult-to-measure constructs such as experience as applied to a range of human capital development (Åstebro et al., 2012), as well as adjustments (and values) associated with academic career trajectories.[25] The challenges raised by such an undertaking suggest an analysis in the style of Trajtenberg's (1990) estimation of the social economic value of computed tomography (CT) scanner patents. One possibility in our setting that mirrors the spirit of the Trajtenberg (1990) approach is to use the estimated values of all patents that cite one prior patent to reflect the social value of that prior patent. We conduct such an analysis in the online Appendix, Table 5.

Our effort is based on commercialization outcomes at a single U.S. research university. While this university is a leading research institution and prolific patenter and licensor, its practices and outcomes may not be fully representative of all academic institutions (especially those outside the U.S.). A more precise empirical model would be calibrated against a nationally and internationally representative dataset of all licensing outcomes (both licensed and unlicensed), and is worthy of future research.

The economic incentives shaped by university patent valuation poses implications for both university and public policies. Recent research has examined whether academic founders might alter their commercialization behavior in response to the financial incentive environment on IP ownership (Lach and Schankerman, 2008; Hvide and Jones, 2018; Oullette and Tutt, 2020). While IP ownership and financial

[24] We also consider a non-parametric Data Envelpement Analyses (DEA) estimation in the Online Table 4, following Thursby and Kemp (2002), Thursby and Thursby (2002), and Siegel, Waldman, and Link (2003).

[25] Counterfactuals (e.g., foregone or added social value from potentially altering the trajectories of academic careers) would also need to be considered.

Table 5

Production Function of Patent Value in U.S. Universities. After finding that university patent value is economically relevant to both patent licensing and startup formation, we analyze the production function of patent value to analyze what inputs are important correlates of valuable patents. The dependent variable *PatVal* is the total value of patents applied for (and later granted to) a university. We consider five basic university characteristic variables, including five-year cumulative R&D expenditures (*R&D*, with a 20% obsolescence rate per year, following Chan et al., 2001), the number of full-time faculties (*Faculty*), a dummy variable indicating whether the sample university is a Carnegie-ranked research university or not (*Carnegie*), and the full-time equivalents (*FTE*) in a technology transfer office (*TTO*). We also consider six additional university characteristics variables, including five-year cumulative NSF grants (*NSF*, with a 20% obsolescence rate per year), five-year cumulative NIH grants (*NIH*, with a 20% obsolescence rate per year), age of a sample university (*Age*), a dummy variable indicating whether the sample university has a medical school or not (*MedicalSchool*), a dummy variable indicating whether the sample university has a business school or not (*BusinessSchool*), and a dummy variable indicating whether the sample university is a member of the Ivy League or not (*IvyLeague*). Panel A reports the correlation among all variables. In Panel B, we report cross-sectional OLS regressions in a log-log form to estimate the Cobb-Douglas production function of patent value in universities.

Panel A: Correlation Matrix

	R&D	Faculty	Carnegie Research	FTE	TTO	NSF	NIH	Age	Medical School	Business School	Ivy League
R&D	1	—	—	—	—	—	—	—	—	—	—
Faculty	0.89***	1	—	—	—	—	—	—	—	—	—
Carnegie Research	0.30***	0.31***	1	—	—	—	—	—	—	—	—
FTE	0.92***	0.90***	0.24***	1	—	—	—	—	—	—	—
TTO	0.08	0.10	0.05	0.06	1	—	—	—	—	—	—
NSF	0.83***	0.89***	0.20**	0.92***	0.07	1	—	—	—	—	—
NIH	0.90***	0.81***	0.23***	0.89***	0.07	0.81***	1	—	—	—	—
Age	0.14*	0.17**	0.22***	0.11	0.11	0.07	0.23***	1	—	—	—
Medical School	0.24***	0.22***	0.24***	0.21***	−0.05	0.15*	0.32***	0.19**	1	—	—
Business School	0.06	0.11	0.26***	0.07	0.10	0.07	0.01	−0.04	−0.07	1	—
Ivy League	0.09	0.09	0.07	0.07	0.04	−0.01	0.14*	0.52***	0.10	−0.18**	1

Panel B: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R&D	0.8655***	—	—	—	—	—	—	—	—
	(0.0494)	—	—	—	—	—	—	—	—
Faculty	—	0.9245***	—	—	—	—	—	—	—
	—	(0.0808)	—	—	—	—	—	—	—
Carnegie Research	—	—	1.2947***	—	—	—	—	—	—
	—	—	(0.1985)	—	—	—	—	—	—
FTE	—	—	—	1.0411***	—	—	—	—	—
	—	—	—	(0.0796)	—	—	—	—	—
TTO	—	—	—	—	0.7860**	—	—	—	—
	—	—	—	—	(0.3170)	—	—	—	—
NSF	—	—	—	—	—	0.8629***	—	—	—
	—	—	—	—	—	(0.0734)	—	—	—
NIH	—	—	—	—	—	—	0.4959***	—	—
	—	—	—	—	—	—	(0.0476)	—	—
Age	—	—	—	—	—	—	—	1.0836***	—
	—	—	—	—	—	—	—	(0.2523)	—
Medical School	—	—	—	—	—	—	—	—	0.9683***
	—	—	—	—	—	—	—	—	(0.2185)
Business School	—	—	—	—	—	—	—	—	—
	—	—	—	—	—	—	—	—	—
Ivy League	—	—	—	—	—	—	—	—	—
	—	—	—	—	—	—	—	—	—
Constant	−2.9508***	−3.4141***	0.3590**	−0.1248	0.5485*	0.3467***	−0.3223	−3.9401***	0.6477***
	(0.2622)	(0.4377)	(0.1615)	(0.1429)	(0.2981)	(0.1301)	(0.1962)	(1.2287)	(0.1844)
Observations	158	147	158	158	158	158	158	158	158
R-squared	0.7508	0.5626	0.1885	0.7170	0.0109	0.4371	0.4827	0.1110	0.1169

(*continued on next page*)

Table 5 (*continued*)

Panel B: Regression Results

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
R&D	—	—	0.4975***	0.4985***	0.4695***	0.4845***	0.5139***	0.4699***	0.4753***	0.4321***
	—	—	(0.1013)	(0.1019)	(0.1120)	(0.1066)	(0.1035)	(0.1020)	(0.1019)	(0.1154)
Faculty	—	—	0.2358*	0.2398*	0.2360*	0.2472**	0.2409**	0.2686**	0.2160*	0.2339*
	—	—	(0.1205)	(0.1238)	(0.1202)	(0.1209)	(0.1206)	(0.1181)	(0.1202)	(0.1197)
Carnegie Research	—	—	−0.2031	−0.2044	−0.2031	−0.2419	−0.2042	−0.1499	−0.1802	−0.1416
	—	—	(0.1718)	(0.1727)	(0.1723)	(0.1801)	(0.1722)	(0.1811)	(0.1754)	(0.1957)
FTE	—	—	0.3656**	0.3693**	0.3540**	0.3574**	0.3793***	0.3645**	0.3808**	0.3706**
	—	—	(0.1479)	(0.1540)	(0.1489)	(0.1498)	(0.1430)	(0.1488)	(0.1476)	(0.1509)
TTO	—	—	0.1523	0.1567	0.1253	0.1152	0.1090	0.1854	0.1314	0.0406
	—	—	(0.1341)	(0.1362)	(0.1464)	(0.1243)	(0.1329)	(0.1808)	(0.1377)	(0.1864)
NSF	—	—	—	−0.0108	—	—	—	—	—	0.0264
	—	—	—	(0.0836)	—	—	—	—	—	(0.0810)
NIH	—	—	—	—	0.0342	—	—	—	—	0.0577
	—	—	—	—	(0.0375)	—	—	—	—	(0.0403)
Age	—	—	—	—	—	0.1555	—	—	—	−0.0141
	—	—	—	—	—	(0.1609)	—	—	—	(0.1664)
Medical School	—	—	—	—	—	—	−0.2000	—	—	−0.2746**
	—	—	—	—	—	—	(0.1228)	—	—	(0.1201)
Business School	−0.1138	—	—	—	—	—	—	−0.3921	—	−0.2504
	(0.4141)	—	—	—	—	—	—	(0.2801)	—	(0.2672)
Ivy League	—	1.5102***	—	—	—	—	—	—	0.6482***	0.6341***
	—	(0.3231)	—	—	—	—	—	—	(0.1850)	(0.2076)
Constant	1.4162***	1.2331***	−2.8502***	−2.8712***	−2.7851***	−3.5207***	−2.7953***	−2.5863***	−2.6928***	−2.2300**
	(0.3994)	(0.1063)	(0.4935)	(0.5219)	(0.5131)	(0.8232)	(0.4829)	(0.5625)	(0.4914)	(0.9367)
Observations	158	158	147	147	147	147	147	147	147	147
R-squared	0.0004	0.0632	0.7992	0.7992	0.8001	0.8011	0.8034	0.8041	0.8115	0.8214

All variables are averaged across sample years for each university. *PatVal, R&D, NSF*, and *NIH* are in $ millions and adjusted for inflation. *R&D* and *FTE* come from the annual reports of the Association of University Technology Managers (AUTM) 1991–2010. *Faculty, NSF*, and *NIH* are collected from the Carnegie reports (1994, 2000, 2005, and 2010). All other variables are collected from internet searches. ***, **, * indicate significance levels of 1%, 5%, and 10%, respectively.

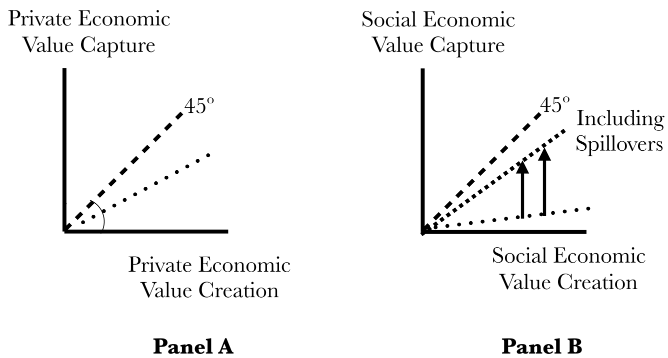

Figure 1. Conceptual Framework of Our Analysis.

incentive sharing policies are not the main subject of our analysis, financial incentives to academic inventors or universities weakened by less economic value capture may shape behavior and subsequently affect the net social benefit from commercializing or spill overs from university research. As we acknowledge above, we are unable to analyze the social welfare effects since it requires valuing academic research effort across commercial and research domains. Nevertheless, we hope that our analysis of university-level patent value correlates helps guide future policy-relevant research.

The goal of our benchmarking approach is to provoke a conversation among university administrators, technology transfer officers, and policy makers regarding commercializing university IP assets. Such a conversation would benefit from a benchmarking exercise beyond the summary (yet simplistic) metrics by which university commercialization performance is often judged. Clearly, a complete understanding and a fair assessment of the economic value generated and captured by universities of their scientific discoveries through patents requires further research and data beyond this initial foray. As the commercialization of university research increases in importance, the tools and methodologies by which we assess such efforts must keep pace.

Credit author statement

All authors contributed equally to this research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

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