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Benchmarking university technology transfer performance with external research funding: a stochastic frontier analysis

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Abstract

Many universities engage in academic entrepreneurship, often with funding from external sources. Benchmarking technology transfer performance with external research funding can help universities identify and learn from peers that may possess strategic advantages in productivity. It also can be key for organizational learning and for communicating organizational performance to policy stakeholders and industry partners. In this study, we construct a unique dataset by linking two important data sources, AUTM and UMETRICS, and use stochastic frontier analysis to benchmark university licensing and revenue performance with different federal funding streams. Our empirical results suggest that universities looking to promote commercialization performance might look to National Science Foundation funding, and the universities best at production (i.e., licensing technologies and generating patents) with external funding are not necessarily the best at capturing benefits from generating revenue from entrepreneurial activity and launching start-ups. Our study points to the importance of the differential advantages of sources of federal research funding and offers implications for policy makers and university administrators.

Keywords Performance · Federal funding · National science foundation · Benchmarking · Stochastic frontier analysis

JEL Codes D24 · I23 · O32 · O38

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1 Introduction

Federal research funding through institutes such as the National Science Foundation (NSF), National Institutes of Health (NIH), and the US Department of Agriculture (USDA), as well as funding from industry, are a critical part of the US federal science policy and technology infrastructure. Universities leverage these external funding sources to produce, co-produce, and directly bring to market critical innovations. This is known as a third role of universities (Ankrah et al., 2013; Barbieri et al., 2018; de Wit-de Vries et al., 2019; Grimaldi et al., 2011; Hayter et al., 2020; O'Shea et al., 2005; and Swamidass & Vulasa, 2009).

The degree to which universities successfully leverage external funding in entrepreneurial efforts is not homogenous (Coccia & Bozeman, 2016; O'Shea et al., 2005; Kim, 2013), so benchmarking can be critical. Variation in performance can be attributed to a series of factors including use of intermediaries, experience, knowledge differences, resources and capabilities, bureaucracy and organizational design, and informational and cultural barriers (De Wit-de Vries et al., 2019; Siegel et al., 2004). Despite the variation, universities can pursue certain strategic advantages that enhance their entrepreneurial ability, and adopting best practices can be critical to improving their productivity and success in entrepreneurial efforts (Siegel et al., 2003). Benchmarking, the process by which organizations scientifically use peer comparisons to facilitate organizational learning and innovation, can thus be critical to adopting best practices that lead to organizational growth and performance improvement (Ammons, 1999; Ammons & Roenigk, 2015). Benchmarking university performance with external research funding is also important for organizational learning and for evaluation by policy makers and technology transfer offices (TTOs).

In this study, we examine if and to what extent federal funding of different sources impacts university technology transfer performance. Our aim is to lend further insights into benchmarking university performance in entrepreneurial efforts (Belitski et al., 2019). A common barrier to this line of research is the lack of nuanced data on external investment/research funding. To address this, we first construct a unique dataset by linking two important data sources: UMTERICS, a unique dataset of federal awards provided by a member consortium of universities anchored by an IRB-approved data repository hosted at the University of Michigan's Institute for Research on Innovation and Science (IRIS), and AUTM (formally known as the Association of University Technology Managers) data on technology transfer.

We then benchmark university entrepreneurial productivity achieved with external funding. Specifically, we disaggregate external funding into different resource streams and use stochastic frontier analysis (SFA) to benchmark university licensing, disclosure, and revenue performance. Our result suggests that while universities use external research funding to pursue several different technology transfer outcomes, performance in one dimension may not imply performance in others. Our study offers implications for both policy makers and university administrators.

2 Theoretical framework

The continuous prominence of the research enterprise at US universities has been complicated by the rising costs associated with research production as well as an increasingly constrained funding environment (Abramo et al., 2009; Coccia, 2008).

Benchmarking the productivity of research funding across institutions and projects and their relative performance has thus become a vital area of inquiry for both academics and practitioners (see Auranen & Nieminen, 2010; Chapple et al., 2005; Grimaldi et al., 2011; Hayter et al., 2020; O'Shea et al., 2005; and (Swamidass & Vulasa, 2009).

Historically, many argue that the Bayh-Dole Act (P.L. 96-517, Patent and Trademark Act Amendments of 1980) transformed the degree to which universities engage in research commercialization strategies, in part by uniformly allowing nonprofit organizations to retain property rights to intellectual advances (Grimaldi et al., 2011; Link et al., 2011). Key provisions involve property rights from externally funded projects with commercial potential such as research funded by the NIH and NSF to be part of entrepreneurial efforts by nonprofits, which include universities. Even before Bayh-Dole, extramural public funding played a key role as a major research input in research-oriented universities (Mowery & Rosenberg, 1999). For instance, NSF funding has played a tremendous role in the development of scientific knowledge and commercialized research (Chen et al., 2013).

As an important input into the research production process, external funding has been heavily prioritized in tenure and promotion policies (Owen-Smith & Powell, 2001), location of local investments and partnerships (Friedman & Silberman, 2003), development of partnerships between universities (Owen-Smith & Powell, 2001), and overall strategic orientation of research-intensive universities (Gardner & Veliz, 2014). It also has positive effects on licensing and patent activity, which is as important for university technology performance as it is for certain industries (Cohen et al., 2002; Coupe, 2003).

While all US research-intensive universities innovate with external funding, significant heterogeneity in performance can exist (Coccia & Bozeman, 2016; O'Shea et al., 2005; Kim, 2013). Simply put, universities can have strategic advantages that better position them to improve technology transfer performance (Chapple et al., 2005; Arora et al., 2019), such as proximity to industry (Lindelöf & Löfsten, 2004), social ties to investors (Wright et al., 2004), and relationships with industries (Bellini et al., 2019). Also, heterogeneity in practices can be substantial and include TTO size (Chapple et al., 2005), IP evaluation processes (Sorensen and Chambers, 2008), use of intermediaries (De Wit-de Vries et al., 2019), standard licensing agreement terms (Siegel et al., 2004), and royalty share to inventors (Jefferson et al., 2017).

Universities can benefit from technology transfer best practice knowledge (Qureshi & Mian, 2020). Given the heterogeneity of university practices in technology transfer and research entrepreneurship (Powell et al., 2007), benchmarking can be a critical tool for universities looking to improve technology transfer practices. The most useful benchmarking practices involve "rigorous procedures for identifying best-in-class performers, analyzing processes, and isolating elements that contribute to excellent results" (Ammons & Roenigk, 2015, p. 314). For universities engaged in technology transfer, effective benchmarking practices entail "enabling the participating organizations to understand how well they are doing relative to peer or similar organizations" (Tornatzky, 2001, p. 270). In practice, technology transfer benchmarking procedures often involve analyzing administrative data to identify historical lead performers from which peer organizations can learn. Given the varied nature of administrative data, benchmarking strategies of technology transfer performance can be diverse and include qualitative (Stone, 2003), descriptive (Heher, 2006), non-parametric (Lafuente & Berbegal-Mirabent, 2019), and parametric techniques (Chapple et al., 2005). However, in the context of university technology transfer performance, few benchmarking approaches emphasize the external resources that most universities use as crucial inputs in the research production process or focus on the disaggregated and different vectors of public funding that universities depend on (Schmiemann & Durvy, 2003).

It is crucial that external funding sources be disaggregated as inputs in benchmarking approaches since universities normally rely on multiple funding sources in research production. These inputs can include resources from different agencies such as the NSF (Bozeman & Boardman, 2004), the NIH (Blume-Kohout et al., 2015), and the USDA (Perko & Narin, 1997; Spielman & von Grebmer, 2006). While previous research has investigated the productivity of overall research expenditures (Heisey & Adelman, 2011), data limitations have typically been a barrier to benchmarking university performance with the different input streams that universities draw from industry, the federal government, and other sources.

Further, universities pursue multiple goals with external funding including social goals, such as developing ideas and research outputs for economic development and the advancement of science (Bozeman et al., 2015), and intrinsic goals, such as generating revenue from licensing technologies in which their research played a role (Ankrah et al., 2013; Heisey & Adelman, 2011). According to the literature, organizations with strategic advantages and/or capabilities in the pursuit of one goal may not necessarily be strategic leaders in other domains (Reficco & Gutiérrez, 2016). In the context of technology transfer enterprises, based on a series of interviews, Siegel et al. (2003) lay out a series of specific goals, among which the most important ones are licenses, revenue from licenses, and patent generation.

The goal of benchmarking is to learn from best practices in producing research with external funding. The literature on university best practices in pursuit of licensing and patent activities is well developed. In general, universities should have robust incentives and support for innovative faculty, well-designed compensation and management systems for TTO staff, and strategies to mitigate differences in institutional logics between universities, communities, and industry partners to facilitate knowledge transfer (Siegel et al., 2003). Universities should also protect and communicate the benefits of patent protections to faculty (Owen-Smith & Powell, 2001). One of the most robust takeaways from the literature is that universities should develop efficient and effective partnerships with industry partners, as such partnerships can be critical to facilitating licensing and patent activities through developing robust knowledge transfer capabilities (Ramos-Vielba & Fernández-Esquinas, 2012). For researchers, university-industry collaboration can be beneficial as well, since it entails the potential of more research funding and a productive division of tasks between researchers and their industry counterparts (Bikard et al., 2019). Additionally, industry experience can benefit the productivity of junior and female researchers (Lin & Bozeman, 2006).

The strategies and practices universities used to generate revenue from commercialization can be different from those used to develop licensing and patent activities. Generating revenue from technology can be difficult for universities, and marketing university sponsored technologies and products can be cumbersome (Lundquist, 1996). The strategic orientation of TTOs can sometimes center around licensing or patenting ideas as opposed to generating revenue, so strategic orientation toward disclosing and/or patenting inventions can conflict with strategies to generate revenue (Swamidass & Vulasa, 2009). The high cost of patenting, for instance, means universities might seek out industry partners to pay for patent applications. Researchers might publish their findings in the meantime, or universities might trade off potential royalties to alleviate patent fees (Klein et al., 2010).

In recent years, many universities have aggressively pursued a fourth commercialization output: start-ups (Swamidass, 2013). The strategies that universities use to develop and support start-ups can be different from the more traditional commercialization strategies. Universities with strong start-up capabilities are best at educating entrepreneurs and supporting new ventures led by academics by offering an array of support in the areas of business education, including strategic, technical, and leadership support for researchers who have spent careers as academic knowledge generators (Eesley & Miller, 2017). In short, instead of facilitating knowledge transfer from universities to industry partners, start-up support involves transferring business knowledge to the researchers themselves.

In this case, there remains meaningful variance across three domains: producing patents, generating revenue from technologies, and launching startups. First, each of these domains requires a different set of strategic capabilities. The best performers in one domain (e.g., patent generation) may be different from the best performance in other domains such as start-up support or revenue generation. A university with an efficient TTO and a robust network of industry partners might be adept at turning external research funding into patents but might be less adept at generating revenue from technologies and capturing value from their partnerships. Accordingly, while there are general best practices universities can adopt, there is much to learn by benchmarking university performance with external funding across patenting, revenue generating, and startup domains.

Second, even though universities can learn about capabilities that matter from the technology transfer literature, there is still useful variance in how best performance might contribute to strategic positions and capabilities. For instance, differences in approaches in TTO operations, university strategic planning, and competitive advantage, geographic location, and incentive structure are apparent in the literature, even if they are more about the pursuit of generally similar best practices (Reficco & Gutiérrez, 2016).

Prior literature suggests that while universities use external research funding to pursue several different technology transfer outcomes, performance in one dimension may not imply performance in others.

3 Study design

3.1 Sample and data

We first combine two data sources, matching institutional entrepreneurship data from AUTM's Statistics Access for Technology Transfer (STATT) database with aggregated individual award data from the UMETRICS database, an emerging database funded in part by the Sloan Foundation and managed by the IRIS Institute at the University of Michigan (IRIS 2019). Using the aggregated award amounts, we then benchmark entrepreneurial performance with SFA, a parametric econometric approach in which productivity is modeled from the residuals of an estimated production function. Last, we compare and analyze the scores across all four models.

The use of AUTM databases is robust in the technology transfer performance literature, but it can be difficult to disaggregate funding sources in conventional data sources. Recent advances in linking administrative records and survey datasets have provided some promising implications (Chang et al., 2019). The current analysis thus connects the UMETRICS data to the AUTM STATT database to examine university entrepreneurial productivity achieved with external funding. The three external funding sources covered are the NIH, the NSF, and the USDA. The combined data help to understand the catalytic mechanisms of external funding on research productivity and commercialization.

The UMETRICS data are a micro-level longitudinal dataset covering transaction- and expenditure-related information of sponsored projects by federal grants of IRIS university member institutions (IRIS 2019; Lane et al. 2015). In its 2019 release, 31 member institutions were documented with 392,125 awards (55% from federal agencies) in the amount of $ 83.5 billion (direct total expenditure) (IRIS 2019). The STATT database compiles the annual AUTM licensing activity surveys with information available across nine different topics pertinent to technology transfer and commercialization of its member organizations: licensing and other full-time equivalents (FTEs), research expenditures, license agreements, research funding related to licenses, license revenue, legal fees expenditures and reimbursements, IP-related activity, start-ups, and licensed technologies (Kim 2013, 186).

Prior to linking the two datasets, 30 institutions with 254 observations were identified from the 2019 UMETRICS core award file covering award information from the years 1900, 1979, and 1999 to 2018. The uneven coverage across institutions is due to the varied membership lengths. For example, only 2 institutions were covered in 2001, but 21 were covered in 2018. In the STATT data, 21 institutions with 510 observations were identified with technology transfer data from the years 1991 to 2016. The uneven coverage can likewise be attributed to the varying number of organizations surveyed each year. The merging of the two datasets resulted in a sample of 12 institutions with 91 observations. Of the 6 institutions excluded in the merging, 5 were technology transfer associations affiliated with existing IRIS member universities, and one was missed due to the year mismatch between the two datasets. Table 1 lists our sample's descriptive statistics.

We also take two steps to alleviate confidentiality concerns associated with the UMETRICS data use agreement. First, we modify the identifiers of universities used to match across the STATT and UMETRICS data. Second, we transform the USDA award count into a binary variable indicating if the count exceeded ten (Table 2).

We acknowledge that our sample is not necessarily a representative one. Both the STATT and UMETRICS databases are membership based: organizations select into data provision in both cases. University TTO members are likely somewhat different than their counterfactual, non-member peers. For example, in our sample the average industry research expenditure amount is approximately $46 million annually. The average amount of industry research expenditures of AUTM in the STATT database members is approximately $19 million (Table 3).

Average outputs are higher as well, as the universities in our sample have higher patent, licensing, start-up, and revenue output. As one might suspect, the universities in our sample are more active overall than the average AUTM enterprise. Still, this design is mostly concerned with the relations between inputs and outputs and the relative productivity across the concerned dimension, so higher-than-average level values should still allow for valid inference.

4 Data analysis

Typically, in SFA, output is modeled as the dependent variable in an econometric, regression-based model where inputs serve as the independent variables and the error term is decomposed into two components, a zero-mean error term typical of what is expected in regression techniques and a term representing inefficiency. In other words, SFA estimates a frontier model, where essentially the output produced is regressed against the inputs used in the production process. SFA is intuitive because to produce output, organizations consume inputs and what remains indicates how well organizations use inputs to produce

Table 1 Descriptive statistics

	NIH expenditures	NSF expenditures	USDA expenditures	TTO FTE	Industry expenditures	Active licenses	Gross licensing revenue	Patents filed	Start-ups
Mean	151,621,978.02	40,742,690.23	11,970,993.96	9.07	46,178,978.29	291.37	36,813,755.02	201.77	8.02
Median	104,000,000.00	35,550,000.00	8,353,448.00	8.00	34,190,733.00	291.00	9,840,844.50	178.00	8.00
Min	20,400,000.00	4,823,572.00	0.00	4.00	3,984,852.00	65.00	836,407.00	33.00	0.00
Max	429,000,000.00	92,300,000.00	48,087,881.00	23.00	127,700,000.00	707.00	360,948,649.00	461.00	26.00
Kurtosis	2.48	2.42	3.34	4.18	2.11	7.06	9.87	2.70	3.78
Skewness	0.92	0.61	1.07	1.28	0.81	1.70	2.70	0.67	0.75
Observations	96								

Table 2 SFA scores

ID	Licenses	Patents	Revenue	Start-ups
10,151	0.727	0.246	0.022	0.214
22,480	0.843	0.430	0.651	0.864
23,402	0.363	0.378	0.488	0.711
8060	0.233	0.259	0.003	0.583
10,075	0.234	0.236	0.003	0.422
10,161	0.526	0.320	0.006	0.783
11,479	0.325	0.374	0.033	0.765
10,171	0.241	0.260	0.038	0.356
22,165	0.434	0.378	0.031	0.793
10,181	0.349	0.297	0.044	0.470
45,700	0.745	0.402	0.058	0.875
87,501	0.904	0.692	0.072	0.884

Table 3 Correlation of productivity scores

	Licenses	Patents	Revenue	Start-ups
Licenses	1			
Patents	0.623	1		
Revenue	0.285	0.338	1	
Start-Ups	0.385	0.768	0.316	1

outputs. The standard model takes the natural log of each input and output in accordance with the Cobb–Douglas production function:

Inputs universities use

$$\log y = \boldsymbol{\beta}'\boldsymbol{x} + v + \mu \tag{1}$$

Outputs universities produce

How well each university turns input into output (productivity)

where $\boldsymbol{y}$ denotes output and $\boldsymbol{B'x+v}$ represents the "stochastic frontier." $\boldsymbol{x}$ represents a vector of inputs, where $\boldsymbol{v} \sim \mathrm{N}\ (0, \sigma)$. Inefficiency is represented by μ, an estimation formed from decomposed residuals typically skewed leftward (negatively), the extent to which organizations' observed output $\boldsymbol{y}$ deviates from the "maximum output" denoted by the stochastic frontier. Unlike most parametric estimation techniques, the primary objective in SFA is not the parameters' effect size and significance, which would denote the degree to which inputs produce output. Rather, the objective is to measure productivity using the error terms (Ruggiero, 1996; Siegel et al., 2003). SFA occurs in two step. The stochastic frontier (***B'x+v,*** that is, output level explained by input amounts) is first estimated. Then the inefficiency of each organization ($\boldsymbol{\mu}$) is estimated using the deviation from the estimated ***B'x+v*** by taking the exponent of the residual since the entireH equation is in natural logs.

Data envelopment analysis (DEA) is also a commonly used tool to measure performance, particularly when there are multiple outputs at stake. In some cases, DEA and SFA performance constructs triangulate similarly (Coupet & Berrett, 2019), yet significant differences can still exist between DEA and SFA performance constructs (Chapple et al., 2005). DEA is a non-parametric mathematical linear program that computes performance scores by optimizing the sum of weighted ratios composed of the multiple inputs and outputs of a production function. It can work well as a benchmarking approach when there are many different inputs and outputs since it reports one score based on the multiple performance ratios (Barnum et al., 2017) and is most useful when researchers seek to amalgamate many different inputs and outputs into one performance score for comparison. However, given that our interest is, in part, in the variance in performance between different activities, we follow the approach of Siegel et al. (2003) and proceed with SFA.

Our data include multiple years of revenue and performance data. We use the approach of George Edward Battese and Coelli (1995) to model the panel. Time poses a difficult question in technology transfer performance models, as it can be difficult to predict if increases in inputs, on average, increase entrepreneurial activity, making appropriate lags difficult to specify (Kim & Daim, 2014). Moreover, it is unlikely that these las are constant across universities or individual research projects. Thus, we estimate our models with a time-invariant specification on efficiency such that efficiency is constant across time and productivity serves as a fixed effect (George E Battese & Coelli, 1992; López-Bermúdez et al., 2019).

We structure our analysis to estimate a general production function of the form in Eq. 2. Following previous research (Siegel et al., 2003), we consider three key activities in three different models: (1) *Patents*, the number of patents filed disclosed by the TTO office; (2) *Active Licenses*, the number of active licenses owned by a university; (3) *Revenue,* the amount of revenue generated by the university portfolio of licenses; and (4) *Startups*, the number of startups generated in an single year.

$$\text{Outputs} = F(\mathit{Staff}, \mathit{NIH\ Funding}, \mathit{NSF\ Funding}, \mathit{USDA\ Funding}, \mathit{Industry\ Funding}, Z) \tag{2}$$

Our key production function inputs also closely follow Siegel et al. (2003). The *Staff* measure is composed of the FTE number of staff in the university TTO office. *NIH Funding, NIH Funding, and USDA Funding* represents the total amount of expenditures sourced in each respective federal agency made by the university. We derive the measures by aggregating individual-level award expenditures in the UMETRICS database at the institutional level, and we derive *Industry Funding* from the AUTM measure denoting the dollar amount of funding received by from industry. Essentially, our *Staff* measure serves as a proxy for labor, and our *external funding* (*NIH, NSF, USDA, Industry*) categories measures of capital. *Z* represents time-invariant, unobservable organizational-level controls such as the culture and legal environment each institution faces.

We begin with the assumption that activity would be driven by the total number of TTO staff; the amounts of NIH, NSF, USDA, and industry funding; and a set of time-invariant organization-level controls. This assumption should hold before a production function is estimated with SFA. Essentially, increases in each factor of production should lead to increases in technology transfer activity. To test this assumption, we run a series of models looking to ensure that, empirically, the relevant inputs are positively correlated with outputs. We want to ensure that the different funding streams universities receive, on average, lead to increased activity. We estimate linear feasible generalized least squares models, with university-level fixed effects, with university research outputs on the left-hand side as dependent variables and external funding (*NSF Funding*, *NIH Funding*, *USDA Funding*, *Industry Funding*) and the size of TTO offices.

We run these models separately using the following equation (Eq. 3):

$$\begin{aligned}\ln(\mathit{Technnology\ TransferOutput})_{ij} =& \alpha_{ij} + \beta_1 \ln(\mathit{Staff})_{ij} + \beta_2 \ln(\mathit{NSF})_{ij} + \beta_3 \ln(\mathit{Industry})_{ij} \\ &+ \beta_4 \ln(\mathit{NIH})_{ij} + \beta_5 \ln(\mathit{USDA})_{ij} + U_{ij} + v_{ij},\end{aligned} \tag{3}$$

where $ln(Technnology\ TransferOutput)_{ij}$ is the natural logarithm of $University_i$'s technology transfer output (i.e., licenses, patents, revenue, and start-ups) in year j; $ln(Staff)_{ij}$ is the natural logarithm of its number of staff; and $ln(NSF)_{ij}$, $ln(Industry)_{ij}$, $ln(NIH)_{ij}$, and $ln(USDA)_{ij}$ represent the funding from the NSF, industry, the NIH, and the USDA, respectively. Firm inefficiency is captured by u_{ij}, and v_{ij} is the disturbance term.

Surprisingly, we find that, on average, increasing NIH funding and USDA funding are not associated with increases with disclosure, licensing, and revenue-generating activity. We find that NSF funding, industry research funding, and TTO office size are positively associated with licensing and revenue-generating activity. As a result, we drop both NIH and USDA funding as inputs for technology transfer activity. We then estimate three SFA models using Eq. 4, one for each measure of technology transfer activity. Following Siegel et al. (2003), we estimate a three-factor log linear Cobb–Douglas production function. Since the structure of our data is a panel, we estimate a stochastic model with organizational fixed effects. The fixed effects are then used to construct a measure of efficiency:

$$ln(\mathit{Technnology\ Transfer\ Output})_{ij} = \beta_1 \ln(\mathit{Staff})_{ij} + \beta_2 \ln(\mathit{NSF})_{ij} + \beta_3 ln(\mathit{Industry})_{ij} + u_{ij} + v_{ij}, \tag{4}$$

where $\mu \sim i.i.d.N(\mu, \sigma^2_\mu)$, $\mu > 0$, and $v \sim i.i.d.N(0, \sigma^2_v)$. The rest of the information remains the same as in Eq. 3. μ is a half-normal constant representing productivity, and its half-normality implies that each university is either on the frontier or below it. In SFA, the standard assumption is that v is an i.i.d error term.

The results of our SFA highlight two important findings. The first comes from the production function underlying our SFA. NSF funds are more closely associated with licenses, patent generation, and start-up formation than industry funding. Conversely, industry funding is slightly more associated with license-generated revenue.

Second, the universities that are best at generating entrepreneurial activity with external resources are not necessarily the best at generating revenue from it. In our four production functions, we assess the productivity in pursuit of four outcomes: licensing, patent activity, start-ups formed, and revenue generated. The productivity scores for licensing (Model 1) and patents (Model 2) are correlated. Model 3 estimates a productivity score regarding the revenue generated from licensing revenues, and the scores are meaningfully correlated neither with the scores from Models 1 or 2. Model 4 examines start-up generation performance, which we find correlates with patent performance but neither are associated with licensing or revenue performance.

5 Findings and implications

Policy makers, including the congressional bodies that fund research agencies such as the NSF, have long been trying to link NSF funding to social outcomes. Benchmarking success(es) with extramural funding streams, particularly those from federal agencies like the NSF and NIH, is critical to the continued advancement of the US public research institutional design. Federal funding to university research enterprises has fluctuated in past decades (Mervis, 2006), and while there is empirical evidence of its potential transformational impact (Arora & Gambardella, 2005; Jacob & Lefgren, 2011), some Congress members have gone as far as to label federal research funding as wasteful (Mervis, 2014). Some of the pressure to reduce federal funding seems to be political in nature as opposed to related to scientific productivity (Mervis, 2013). Such fluctuations may persist, and it is important for universities to maximize productivity with federal funding. Thus, as the research offices that often coordinate technology transfer enterprises look to improve performance and productivity with extramural funding, learning from the practices, capabilities, and strategic advantages of their peers can be key to managing performance and charting strategic directions.

The structure of our data and the nature of technology production functions make causal approaches difficult, but our findings join a growing chorus of research and data science initiatives suggesting public research funding is a critical driver for research production. Research in the technology transfer domains focuses heavily on industry partnerships and industry funding, and while our findings suggest that industry funding matters, they also underscore the role of NSF funding.

Relative to NSF funding, NIH and USDA funding does not seem to play a major role in technology transfer production for the universities in our sample. These funding streams are critical to both universities and the communities they serve for many other reasons, such as public health and medical advances as well as agricultural development. Commercialization with NIH and USDA funding may take a backseat to educational, public, and community goals. Our findings *do not* suggest that these two funding streams "matter" any more or less than NSF funding. We interpret this as evidence that universities looking to cultivate entrepreneurial productivity might find, on average, a particularly productive resource in the form of NSF funding. This is a potentially important finding since questions about the productivity of NSF funding has been part of public discourse for some time (Mervis, 2013). While NSF, NIH, and USDA funding are likely important for other social goals, our findings serve as preliminary evidence that NSF funding can help universities both commercialize research and generate revenue.

Moreover, NSF funding seems to be more closely associated with patent, licensing, and start-up activity than industry funding. While the difficulty and variance in production lags makes causal inference difficulty in estimating these production functions, the fixed effects models used in this study controls for time-invariant organizational variables, and our findings at least suggest that NSF funding is as productive at industry funding in facilitating research commercialization patent, licensing, and start-up outcomes. It also appears to be nearly as important to revenue generation as industry funding. Universities pursue industry partnerships to build revenue streams (Berbegal-Mirabent et al., 2015), but these results suggest that NSF funding might help facilitate revenue generation from commercialization activity as much as external industry funding.

Our findings suggest that universities looking to benchmark their own performance should find peers and generally benchmark in *each* of the relevant domains. After the

Bayh-Dole Act, university strategic orientation and process optimization has been mostly focused on licensing and patents. Generating revenue seems to be a different beast, and start-ups are a frontier in the sense that many university systems and TTOs are still developing strategies for success (Crișan et al., 2019). In our sample, performance in the traditional areas (licensing and patents) is only weakly correlated to revenue and start-up performance. TTO enterprises and university strategic initiatives should perhaps identify aspirational peers in each domain. No university in our model scored as a top performer in each model. Rather, universities were strong in some and relatively weak in others.

Universities looking to peers for organizational learning should perhaps seek out peers in the different strategic groups that make up the multiple missions. Universities manage or partner with TTOs to commercialize research, and while it is well known that this goal should be balanced with educational, public, and community goals, researchers should consider that the different goals within research commercialization itself might require different strategic organizations. In short, universities produce and manage many outputs and strategic goals with external funding, and the peers from which they might garner best practices might be different based on those different goals.

While our study is not the first to use the emerging UMTERICS data initiative (Allen et al.2015; Buffington et al., 2016), future research in technology transfer performance may leverage the data as they grow. Future research might use productivity measures, such as these and those produced by other benchmarking techniques, to investigate what best practices and strategic factors lead to strategic advantage in leveraging external funding for research. Research funding does more than produce market-oriented outcomes, and the social and public value created by academic innovation is an increasingly important consideration (Bozeman et al., 2015). We do not consider all of the wide array of social outcomes here, but with the growth of data partnerships such as IRIS, valid constructs of social value may be become more widely available. Techniques such as SFA can be used to benchmark them as well.

As Bozeman et al. (2015) additionally note, our activity-oriented model says little about downstream outcomes and overall impact of investment in R&D. We only benchmark the degree to which universities can transform external funding into quantifiable activity-based outputs. Our model is university centric, and we do not spotlight the impact these technologies have on communities. We do leverage the UMETRICS data in this study, which have promising potential to study downstream effects and impact R&D funding. Buffington et al. (2016), for instance, use UMETRICS data to link STEM training to early career outcomes for male and female students. We bind this study to a benchmarking study for universities, but the UMETRICS data might have important implications for downstream effects of R&D funding.

Our use of both the AUTM and UMETRICS data introduced some limitations into the study. First, our sample size is a snapshot of the TTOs and university entrepreneurship offices remitting data to both AUTM and UMETRICS. The UMETRICs is still emerging, so we were constrained in this regard. Still, the UMETRICS initiative is growing, and we encourage scholars interested in extending the generalizability of this study to consider the UMETRICS data's capabilities as the initiative grows. Additionally, our data use agreement restricted use of the data to portions that would not compromise the anonymity of institutions remitting data to UMETRICS. Thus, certain institutional characteristics that would, when combined with portions of the data necessary to estimate a production function, compromise this anonymity were not available to us.

These include data on the presence of a medical school. There is limited evidence that having a medical school is related to tech transfer performance (Heisey & Adelman, 2011;

Siegel et al., 2003), but it is possible that TTOs also supporting medical schools have production functions with different structures. In our study, this might most manifest in our finding that NIH funding does not a seem to be a major driver of productivity. A disaggregated production function of TTOs at universities with medical schools might produce a different result. Related to this, SFA also assumes that every decision-making unit (university TTOs) have a shared production function. Further, our particular model assumes constant efficiency over the data periods (Belotti et al., 2015). Future models using a larger dataset might allow for future research investigating changes in productivity with external funding over time (Greene, 2005; Kumbhakar & Lovell, 2003).

6 Conclusions

In this study, we benchmark university performance with external funding across four main areas of technology transfer productivity: licensing, patents, start-ups, and revenue generated. Using SFA, we estimate performance measures across these main areas and find that the link between NSF funding and technology transfer performance are at least as strong as the link to industry funding and Tech Transfer performance. Comparing performance across these domains, we also find that universities that perform well in one domain are typically at best weakly linked to others, particularly regarding start-ups in revenue. Simply put, high performance in licensing and patent domains does not necessarily imply high performance in generating revenue or launching start-ups.

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Declarations

Conflicts of interest The author that they declare no conflicts of interest.

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