The Effects of Academic Incubators on University Innovation

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Research summary

In this paper we analyze the impact of academic incubators on the quality of innovations produced by US research-intensive academic institutions. We show that establishing a university-affiliated incubator is followed by a reduction in the quality of university innovations. The conclusion holds when we control for the endogeneity of the decision to establish an incubator using the presence of incubators at peer institutions as an instrument. We also document a reduction in licensing income following the establishment of an incubator. The results suggest that university incubators compete for resources with technology transfer offices and other campus programs and activities, such that the useful outputs they generate can be partially offset by reductions in innovation elsewhere.

Managerial summary

Do university incubators drain resources from other university efforts to generate innovations with commercial relevance? Our analysis suggests that they do: after research intensive US universities establish incubators the quality of university innovations, which we measure with patents, drops. This finding has immediate implications for practice as it suggests that the benefits and costs of incubation should not be analyzed in isolation. Rather, the effects of incubators extend to the overall innovation performance of the university. It follows that measuring the net economic effect of incubators is challenging because besides the effects on innovation efforts the presence of an incubator may attract particular kinds of faculty and students, enhance the prestige of the university, generate economic multiplier effects and benefit the community as a whole.

JEL: C23, C26, L26, O31, O32

Keywords: Incubators, patents, innovation, forward citations, licensing

1. INTRODUCTION

Universities are increasingly tasked with fostering entrepreneurship and innovation, encouraged to generate revenues from research produced on campus and contribute to (local) economic growth (Etzkowitz, 1998, 2002; Etzkowitz et al., 2000; Goldstein and Renault, 2004). This view of the entrepreneurial university reflects two recent trends. First, universities are increasingly patenting research with commercial potential and subsequently seeking to increase their licensing revenues (Bulut and Moschini, 2009; Henderson et al., 1998). At the same time, universities are creating incubator facilities to assist faculty members, university graduates, community members, or other parties to start new firms that not only contribute to local economic growth, but also generate income for the university which often holds equity positions in the incubator's tenant firms.

Establishing university incubators and increasing university patenting reflect similar underlying pressures: both are driven by reductions in public funding for academia and increasing pressures for public accountability. Moreover, the resources and capabilities used to support start-ups and to generate patented inventions are largely shared; maintaining these two activities simultaneously involves leveraging the same academic knowledge and talent, devoting dedicated personnel for patent-issuing procedures and auxiliary services to start-ups, as well as directing significant investments for research equipment that can be used not only by university faculty and staff but also by incubator tenants. By extension, the overlap of goals and resources between university patenting and incubators suggests that decisions to increase university revenue and contribute to innovation and local economic growth through the twin channels of patenting and incubator activities are connected. This observation calls for reflection upon the basic, yet unexplored,

question of how each channel affects the other. In this paper we address that question by examining empirically whether the quality and economic value of university innovation efforts is influenced by the creation of incubator facilities at research-intensive US universities.

Theoretically, the creation of incubation facilities can improve the quality and economic value of university patents by facilitating knowledge flows between academic inventors and market participants, knowledge that can not only help university patents articulate the commercial value of their inventions but also help generate ideas to university inventors that lead to valuable patents. Moreover, assuming that industry–academia collaboration often yields superior outcomes, incubators can lead to higher-quality patents if incubator tenants collaborate with university inventors. On the other hand, the presence of an incubator can reduce the quality of university patents if auxiliary incubator services and patenting activities compete for the same scarce university resources such as funds and dedicated personnel. Similarly, the average quality of university patents may fall once an incubator is in place if the university's overall focus and associated investments and resources shifts towards, say, start-ups over high-quality patenting. Our research aims to see which effect outweighs the other.

We must keep in mind, however, that the decision to establish an incubator can be endogenous; if incubators are followed by increases in patent quality, this could indicate that universities with good projects in the pipeline, and the prospect of high-quality patents down the road, choose to establish an incubator, even though there is no direct effect of incubators on patent quality. Likewise, a decline in patent quality following the establishment of an incubator could indicate that the university expects patent quality to decrease, and establishes an incubator as an alternative mechanisms for generating revenue and fulfilling its entrepreneurial mission.

Theorizing about the connection between incubators and patent quality and empirically testing that connection have not, as far as we are aware, been addressed in previous work. We also

add to the literature on the quality of university patenting which, in addition to insightful, mainly descriptive historical accounts (Henderson et al., 1998), has focused primarily on the effects of regulatory interventions such as the Bayh-Dole Act and the impact of university experience and other university-specific features (e.g. Mowery et al., 2002; Mowery and Ziedonis, 2002; Owen-Smith and Powell, 2003; Sampat et al., 2003).

Our empirical work follows convention in approximating quality. First, we proxy for the scientific and economic value of a patent by recording the number of times a given patent is cited by subsequent patents (forward citations), adjusted for the age of the patent (e.g. Harhoff et al., 1999; Lerner, 1994). Using a large sample of university patents, we then run a series of regressions comparing patent quality before and after the university establishes an incubator, controlling for patent-, university-, and time-specific characteristics that may affect patent quality. To mitigate the aforementioned endogeneity, we also run instrumental-variables regressions; our identification strategy builds on the insight that universities compete with each other and tend to imitate their peer institutions, particularly those that are geographically close (Rey, 2001). Hence, we use the presence of incubators at similar, nearby (and potentially competitor) universities as an instrument for the focal university's decision to establish an incubator. As an additional robustness check, we change the unit of analysis to the university and estimate how the establishment of incubators affects licensing income, a primary goal of university patenting. We describe this exercise in more detail below.

To build our dataset, we collect information on all 55,919 patents granted from 1969 to 2012 to US-based universities that were members of the Association of American Universities (AAU) as of the end of 2012. These universities are research-intensive, they patent extensively, and those that have established incubators have done so in different years, which allows enough time variation in our sample.

Our results suggest that, in terms of generating useful innovation, the value-added of university incubators may have been overstated: we find a strong negative association between the establishment of an incubator and the quality of patents produced subsequently by that university. This relationship holds across a variety of empirical specifications, using different control variables, adding indicators for university and year, and controlling for endogeneity using the instrument described above. At the university level, we find that licensing revenues fall following the establishment of an incubator, controlling for university characteristics such as the size and experience of the technology-transfer office and the average quality of the university's patents. Licensing revenues accrue both to patented and non-patented innovations, and not all patented innovations are licensed, so this can be regarded as an independent test. In other words, not only do university attempts to encourage innovation and entrepreneurship by incubating businesses seem to reduce the quality of subsequent scientific and technical innovations, but they also appear to reduce the income generated by innovative activities.

Moreover, we find that the negative association between patent quality and the establishment of an incubator is larger for universities with less resource munificence (measured by research funding). This is consistent with the idea that resource constraints are driving our results. Fostering startup companies requires financial, human capital, and organizational resources (Powers and McDougall, 2005), and the more resource-constrained the university, the more likely that budgets, facilities, and personnel supporting business incubation are withdrawn from other campus activities that support innovation.

Our findings have important policy implications. University administrators, technology transfer office officials, and other stakeholders generally show a keen interest on the effects of incubators and university patenting (Carlson, 2000; Guy, 2013). This interest is understandable because

patenting and incubation are two prime means for universities to fulfil their new roles of generating economic growth and securing income. If these two means compete for similar scarce resources, then establishing an incubator may, on balance, reduce the quality of the innovative outputs produced by the university. Our work suggests that these innovation channels should be treated jointly, as alternative, and potentially competing, means of fostering innovation and economic growth. In sum, adopting a new lens via which incubation and patenting are analyzed jointly can help decision makers in determining the most effective means for academic institutions to meet the expectations that arise from their new roles.

We organize the rest of the paper as follows: In the next two sections we review the relevant literature and develop our theoretical expectations on the effects of incubators on patent quality. In Section 4 we describe our econometric model and estimation procedures, and in Section 5 we review the data we use. In Section 6 we present the estimation results. Finally, we conclude in Section 7.

2. UNIVERSITY EFFORTS TO FOSTER INNOVATION AND ENTREPRENEURSHIP

Universities have long been central to the innovative process through generating, codifying, and communicating basic knowledge. Since the middle of the 20th century, universities have also played an increasingly important role in developing and using applied knowledge, particularly in the scientific and technical fields (Henderson et al., 1998; Mansfield, 1991, 1995). Universities often serve as "anchors" in the emergence of technology clusters (Stanford University being the best-known example) (Swann and Prevezer, 1996). Universities train scientists and engineers, partner with established and emerging technology firms, and develop their own in-house technologies. The desire to increase universities' applied research outputs and give them a stronger role in the innovative process has led US policymakers to describe local economic development as a

"fourth mission" of the public research university (along with research, teaching, and service) (Etzkowitz et al., 2000; Youtie and Shapira, 2008).

Universities also attempt to foster innovation and economic development directly by establishing business incubators. Business incubators ("incubators" for short) are organizations that help aspiring entrepreneurs translate ideas into profitable ventures. Incubators typically provide office space, consulting services, assistance in finding suppliers and distributors, access to venture capitalists and business angels, and sometimes direct financial support (Aernoudt, 2004; Finer and Holberton, 2002; Rothaermel and Thursby, 2005a). Incubators are operated by a variety of private and public actors including government agencies and NGOs, but more than half of US incubators are affiliated with higher-education institutions (Powell, 2013). University incubators (also called university technology business incubators or UTBIs) provide additional services to their tenant firms such as access to university labs and computing facilities, student workers, and faculty consultants (Mian, 1996). Their on-campus or near-campus location and close relationships with university personnel also make it easier for university faculty and students to establish their own ventures and become incubator tenants.[1] By 2013 all but ten of the US AAU universities had established a campus incubator. Journalist Nicholas Thompson (2013) wrote of Stanford: "Students can still study Chaucer, and there are still lovely palm trees. But the center of gravity at the university appears to have shifted. The school now looks like a giant tech incubator with a football team."

Another approach for encouraging university innovation is to assist faculty, staff, and students in patenting innovations developed within the university. The prospect of a patent provides

[1] In emerging economies, incubators provide even more foundational support, helping firms establish basic supplier and customer relationships, write and enforce contracts, and so on – helping to establish market institutions rather than developing specific business capabilities (Dutt et al., 2013).

an important financial incentive for university personnel to devote time and effort to potentially valuable commercial technologies (Lach and Schankerman, 2008; Owen-Smith and Powell, 2001; Thursby et al., 2001).[2] To facilitate patenting, many universities have established technology transfer offices to ease the administrative burden of the patent application process and to manage the use of patents that are successfully obtained. Most often the university itself will be the patent holder, sharing licensing income with individual scientists; in a few cases, faculty members retain patent rights. The Association of University Technology Managers (AUTM), which represents technology transfer offices, reports that universities earned $2.6 billion in license fees in 2012. Of course, not all innovations are patentable, and not all patentable ideas are innovative. Nonetheless, patents serve as a useful proxy for (quality of) innovation (Acs et al., 2002; Igami, 2013), so we can draw inferences about the strength of a university's innovative programs by examining its portfolio of university-owned patents.

There is a large literature on the use of patents and patent citations as proxies for innovation. Importantly, "innovation," as famously characterized by Schumpeter (1934), includes not only the introduction of new products and services, but refers also to the establishment of new production methods, new sources of supply, new consumer markets, and new methods of organization. Nonetheless the innovation literature has tended to focus more narrowly on technological innovation and to rely on patents as reasonable indicators of innovation (Acs et al., 2002; Igami, 2013). We follow that convention here.

[2] Others have reached opposite conclusions about the incentives of academics to commercialize their research (Colyvas et al., 2002; Markman et al., 2004). More generally, a number of contributions have empirically shown that patents have a financial value (e.g Hoenen et al., 2014; Hsu and Ziedonis, 2013).

Like most of the recent literature on technological innovation, we focus on patent quality, not quantity. Citations of patents by future patent applications ("forward patent citations") are commonly used to measure scientific quality (Harhoff et al., 1999; Igami, 2013; Park and Steensma, 2013). The intuition behind the forward-citations measure is that higher citation levels imply superior scientific significance or applicability. Indeed, studies have consistently shown that forward citations correlate strongly with realized market value for a particular patent (e.g. Harhoff et al., 1999; Lerner, 1994).[3] Of course, citations are not perfect measure of patent quality, just as citations to academic papers and journal impact factors do not perfectly capture the research quality (Costas et al., 2015; Ke et al., 2015; Wang et al., 2013). It is though conceivable that the presence of patent examiners, along with other aspects of the patent review process, may reduce the citation biases associated with academic publishing.

Patent-citation measures must be used with care. More recent patents tend to receive fewer citations largely due to the effective time needed before they become visible. In the same vein, the secular increase in the annual number of patents over time implies that very early patents may also tend to have fewer citations than more recent patents, mostly because patents tend to receive the bulk of their citations in the first few years after issue. Other things equal, then, earlier patents should have fewer forward citations than later patents simply because there were fewer other patents available to cite it (Lanjouw and Schankerman, 2004). As we explain in section 4, we take these observations into account when specifying our empirical model.

[3] Kotha et al. (2013) find that each additional forward citation, other things equal, increases the likelihood a university patent will be licensed by 2 percent. Moser et al. (2015) show how forward citations correlate with objective measures of innovation in plant genomics. For additional evidence that patent value is well approximated by forward citations see recent work on patent auctions, a direct setting for measuring patent value; this work shows that forward citations are a strong predictor of the auction price paid to acquire a patent (Fischer and Leidinger, 2014; Sneed and Johnson, 2009).

3. THEORY AND HYPOTHESES

How could the presence of a university incubator affect patent quality? Our analysis begins with the observation that universities, like other organizations, are bundles of resources, routines, and capabilities (Barney, 1991; Montgomery and Wernerfelt, 1988; Penrose, 1959). A university incubator or other commercialization program does not operate in isolation, but is part of a university's overall portfolio of innovative activities (Powers and McDougall, 2005). From a resource-based or capabilities perspective, the creation of an incubator will have a positive net effect on university innovation if it leverages resources and capabilities that are not fully exploited by the university's other innovative activities such as research facilities and personnel and the technology transfer office (Lockett et al., 2005). Some university resources, such as land and buildings, are not easily divisible, creating the potential for excess capacity. Establishing an incubator can be an effective way of leveraging underutilized resources.

The presence of a university incubator can also create value by encouraging knowledge flows between academic researchers, students, and commercial firms that become incubator tenants (Rothaermel and Thursby, 2005b), increasing the likelihood of university personnel developing valuable, patentable innovations. Moreover, the presence of an incubator reduces the marginal cost for university personnel to establish their own ventures and become incubator tenants, increasing the incentives to generate high-quality patents. Over time, these knowledge flows and learning effects suggest that innovative capabilities may increase. For all these reasons, the presence of a university incubator could lead to higher quality, patentable innovations, suggesting a positive relationship between the establishment of a campus incubator and the patent citations flowing to the focal university.

On the other hand, if universities are resource constrained, and the effects of competition for resources outweigh the benefits of encouraging knowledge flows and capability development,

then university innovation efforts can have a negative effect on some innovative outcomes. Thursby and Thursby (2007: 622) note that [m]any, if not most university licensing endeavors are a net drain on university resources." Incubators, likewise, can be costly to establish and maintain. Buildings must be constructed or expanded and operated, personnel and operating funds must be allocated, faculty time is needed, and so on. These resources could also be devoted to other campus organizations and activities that encourage innovation, such as research facilities and personnel, training, and the technology transfer office. If the opportunity cost of devoting these resources to an incubator outweighs the benefits from incubation, the net effect of the incubator on university-based innovation will be negative. In short, the presence of an incubator could drain resources from other campus activities that encourage innovation, leading to lower-quality patenting.

More generally, evaluating the net effect of university business-incubation programs on innovation provides insight into the nature and utilization of university resources and capabilities, both tangible and intangible. Finding that incubation programs produce higher-quality or more valuable innovations would suggest excess capacity in that the university's existing innovation-related resources and capabilities—including tacit knowledge—such that diversifying into related activities such as incubation generates economies of scope (Montgomery and Wernerfelt, 1988; Penrose, 1959). The opposite finding, that incubation efforts lead to lower-quality or less valuable innovations, suggests that some key resources cannot be leveraged for incubation and the university is externally resource constrained, so that net innovation falls with related diversification.[4]

[4] Our empirical approach, described in detail below, includes average patent quality and licensing income (as a proxy for the total economic value of patenting) as output measures. Because we do not have effective measures of the inputs devoted specifically to patenting—we can measure the size of the technology transfer office but cannot disaggregate university expenditures on faculty, staff, research facilities, and other resources into those devoted to patentable innovations and those devoted to other academic pursuits—we cannot use innovation efficiency as our dependent variable.

Of course, patent quality and value also depend on a host of university-specific factors such as the quality of the technology transfer office and the university's legal staff, the attitude of the administration toward commercialization, and the overall culture of the university. We try to control for these factors, both observable and unobservable, in our empirical work, so that the results can be interpreted as a test of the resource-based argument described above.

The theoretical literature on university innovation does not offer much guidance about the presence and magnitude of these effects, so we turn to the data to examine the net effect of establishing a university incubator on innovation. Using patent quality as our measure of innovation, our main hypothesis is as follows:

> *H1: The presence of a university incubator increases the quality of university-owned patents, other things equal.*

The alternative hypothesis is that incubators and patent quality do not work in tandem, but work against each other, in which case we would find a negative relationship between the presence of an incubator and patent citations, other things equal.

4. METHODS

The general form of the empirical model we specify to test the two competing hypotheses is:

$$y_{it} = X_{it}\beta + \sum_{i} a_i A_i + \sum_{t} \gamma_t \Gamma_t \qquad (1)$$

where y_{it} refers to the number of forward citations through the end of 2012 received by a given patent submitted by university i in year *t*, divided by the number of years since the date the patent was granted (FORWARD). X_{it} is a vector of explanatory variables described below. The summation symbols represent university-specific and year-specific dummy variables.

4.1 Variables

In our main set of regressions, the unit of analysis is the patent, and our primary dependent variable is forward citations per patent. To test the impact of incubators on patent quality we include a dummy variable (INCUBATOR) that takes the value of 1 if the application date of the focal patent is after the opening date of the university incubator and 0 otherwise. For universities that never established incubator facilities, the variable at hand takes the value of 0 for all patents. A positive sign of the associated coefficient would provide support for the hypothesis that incubators increase patent quality, while a negative sign would indicate the opposite.

Following previous literature (e.g. Czarnitzki et al., 2011; Sapsalis et al., 2006) we include several control variables in the analysis. First, we add the number of inventors and assignees in a given patent (INVENTORS, ASSIGNEES). Collaborative efforts generally enhance patent value, so we expect positive signs on the coefficients of both variables. To test whether there are moderating effects between the two variables we add their interaction as an additional regressor. We also include five patent-specific variables. The first measures the number of non-patent references (academic literature, government reports, and so on) included in the focal patent (NON-PATENTREF). The second depicts the number of patents listed in the references list of a given patent (PATENTREF). Based on previous findings we expect non-patent references to be negatively associated with patent quality and the opposite for patent references (Sapsalis et al., 2006). Moreover, because patents that span a wide range of fields are often more valuable than more narrowly focused patents, we include the number of different four-digit International Patent Classification categories assigned to the focal patent (SCOPE) as an indicator of scope (e.g. Gans et al., 2008; Harhoff et al., 2003). We expect a positive sign on the coefficient for scope.

Patents that incorporate more applied knowledge, or borrow from different scientific fields, may also accumulate more forward citations precisely because more inventors may build on

them. To account for such observation we include two dummy variables that take the value of 1 if the patent is classified as biotechnology or information & communication technology-related respectively (BIOTECH and ICT), 0 otherwise. Both scientific fields in question have immediate commercial applications while building on different knowledge bases (see Pisano, 2006 for the case of biotechnology) which is why we expect them to have a positive relationship with the dependent variable.

Prompted by previous findings that experience in patenting generates tacit knowledge and capabilities and is instrumental for university patent quality (Mowery et al., 2002), we also include two variables to capture university experience. The first variable, EXPERIENCE, measures the number of successful patent applications submitted by the focal university in the year before the application date of a given patent. We expect a positive sign for this variable. Besides capturing knowledge and capabilities, this variable also indicates the total patent activity of the focal university, which helps control for diminishing returns (as the number of patents generated by the university increases, the quality of the marginal patent likely decreases).[5] The second variable, FOREXPERIENCE, is designed to capture the university's experience in producing quality patents. It measures the average number of lifetime forward citations per year garnered by the applications, once they are granted patent rights, used to construct the EXPERIENCE variable. Given path dependencies (Teece et al., 1997), we expect a positive sign for this variable.

Finally, we include a set of university-specific dummy variables to account for unobservable characteristics of particular universities that might influence the quality of their patents. These

[5] We choose a one-year lag to capture contemporary effects and to account for diminishing returns, which we expect to occur in a short time. Specifically, as we also explain below, the values for the experience variables at $t = 0$ are similar to those at $t - 1$, letting us better control for contemporary effects that can lead to diminishing returns. Still, when specifying different lags, we do not observe major changes to our estimates.

include the underlying quality of the university faculty, the organizational structure of the academic institution, the effectiveness of rewards that encourage patenting, and the general attitude among the faculty members towards the commercialization of research via patenting.[6] Along the same lines, to account for year-to-year fluctuations that can also influence patent quality we incorporate in the analysis a set of year-specific dummy variables that match the publication year of the focal patent.[7] Such fluctuations may reflect, for instance, the spinoff activity of the focal university which may influence patent quality as firm formation and patent quality draw upon the same depleting resources. Along the same lines, the year dummies also account for the aforementioned observation that the secular increase in the annual number of patents over time may translate to less citations for early patents because there are only few other patents available to cite it (given that most patents receive their citations within a short window after issue).[8]

Before presenting our data and sources in detail we note two significant considerations that relate to our modeling choices and the overall study design. First, we include in our sample only incubators with a physical presence on campus (i.e., a standalone building or location in another university building) whose primary function is to assist faculty members with entrepreneurial projects and are formally tied to the particular university.[9] We exclude from the analysis "virtual"

[6] We considered including additional measures of university quality such as the number of faculty awards and the number of faculty who are members of the Academy of Science. We decided to use dummy variables because consistent, comprehensive data on university quality from such sources as the National Science Foundation, AUTM, and the *Chronicle of Higher Education* are available only for the later years of the analysis. Including such variables reduces our sample by more than half. Also note that in our dataset 42 universities account for more than 85 percent of the observations. We limit the university dummies to those universities.

[7] In our dataset 20 years account for almost 80 percent of the publication years. We limit the year dummies to these years.

[8] Note that all our covariates are measured at the time of patent award. In principle, we could include some time-varying covariates, e.g., for university quality, in case a change in the reputation of a particular university affects citations to previous patents held by that university. We do not expect adopting this model structure to have a substantial impact on the findings.

[9] This is not to imply that such incubators only host faculty entrepreneurs but to emphasize that faculty entrepreneurs tend to be core in the cohort of incubators we study.

or “soft” incubators that typically assist recent graduates in starting businesses by providing small soft loans. We focus on physical, campus incubators based on a) the theoretical expectation that these types of incubators are more likely to be sharing university resources with activities that could also support patenting (leading to a negative relationship between incubators and patent quality) and b) the behavioral assumption that these types of incubators are more likely to generate knowledge flows towards university-based investors (leading to a positive relationship).

The second consideration refers to our definition of “university” we employ and the implications of that definition for our empirical strategy. For universities with one main campus, which comprise the majority of the academic institutions in our sample, the definition is straightforward. For universities that are part of a system (in particular, the University of California and State University of New York systems), the unit of analysis could be either the system or the individual campus, as long as the latter is an AAU member. There are practical implications of adopting each definition. If there are significant knowledge flows across campuses within system universities, and if patenting or/and incubation activities are influenced heavily by the central administration, then treating campuses from the same system as one university seems appropriate. Defining universities by campus emphasizes local-decision making but assumes that knowledge flows and overall direction are confined within campuses. In our baseline estimates we consider each system campus as a separate academic institution. Even when we define a system as a university the results remain qualitatively similar.[10]

[10] A drawback of treating each system as a university, and assigning patents to systems rather than individual campuses, is that systems include campuses that are not AAU members (the University of California system campuses at Merced, Riverside, San Francisco, and Santa Cruz, and the SUNY campuses at Albany and Binghamton).

4.2 Identification strategy

Our analysis explains patent quality in terms of the presence of incubators, university-specific features, and university dummies that proxy for the scientific talent of university faculty, which should also influence patent quality. However, faculty quality at a given university typically varies over time, from learning by existing faculty and the addition of new faculty. As such, university-specific dummy variables may not fully capture scientific talent over the sample period. This creates an endogeneity problem if scientific talent is related to the establishment of incubators (i.e. universities establish incubators only when they have promising faculty or projects in house or as an alternative mechanism for generating revenue and fulfilling their entrepreneurial mission when faced with lesser quality talent) and scientific talent is not adequately measured (with the unobserved part ending up in the error term). To account for such potential endogeneity, we need an instrument that is correlated with the decision of a given university to establish an incubator and uncorrelated with the scientific talent of the focal university.

To construct the instrument we exploit the fact that universities, like other organizations, are highly isomorphic—they are strongly influenced by the behavior of their peers (Meyer and Rowan, 1977; Powell and DiMaggio, 1983; Stensaker and Norgård, 2001). A university is more likely to establish an incubator if its peers (actual or aspirational) are doing the same. We thus construct an instrumental variable for the establishment of each university's incubator at time *t* as the number of incubators established before time *t* at peer institutions.[11] We define peer institutions as those sample universities in either the same state as the focal university or an adjacent

[11] Here we follow the empirical literature on corporate structure, in which diversification, vertical integration, and similar behaviors are analyzed with peer behaviors as instruments—e.g., the number of same-industry firms that are already diversified as an instrument for the focal firm's decision to diversify (Campa and Kedia, 2002; Klein and Saidenberg, 2010).

state. We do so based on findings demonstrating that universities compete with, and are influenced by the decisions of geographically close institutions (e.g. Gonzalez Canche, 2014; McMillen et al., 2007).[12] The presence of incubators in nearby institutions may influence the decision to establish an incubator, reflecting a form of institutional isomorphism, but should be unrelated to the scientific talent of the focal university.

Still, location in the same state or a neighboring state is not a perfect definition of a peer institution. However, by and large, all the sample universities (as AAU members) are of considerable size, prestigious, research-intensive universities, so we are drawing from a fairly homogeneous population. Another potential problem is that a neighbor incubator may draw resources from the focal firm (e.g., Stanford establishes an incubator, so high-quality faculty migrate from UC-Berkeley to Stanford, thus affecting the quality of Berkeley's patents). As noted below, we control for university quality, which should pick up the effects of such faculty migration. Anecdotally, we do not expect this to matter much, as in our sample patents we observe relatively little mobility among patent-holders. A more difficult problem is the potential for researchers at the focal university to collaborate directly with colleagues at a neighboring school, such that the establishment of an incubator at the neighbor affects the research activities of the faculty at the focal university. Again, anecdotally, we do not think this is a major issue, given the ubiquity of collaborations among geographically dispersed faculty members. Moreover, as we explain in section 6, the instrument performs well in our empirical tests.

[12] For instance, McMillen et al. (2007) reveal that the market for college students is in large part shaped by how close other similar universities are as net tuition is inversely related to distance between institutions and Gonzalez Canche (2014) report similar findings in the context of the non-resident student market.

5. DATA

In our baseline regressions the unit of analysis is the patent. To construct our sample we begin with the 62 members of the AAU as of 2012. We excluded the two Canadian members of AAU to have a set of universities more comparable in terms of the motives and means to support incubators and licensing. Of the remaining 60 universities, 6 are members of the University of California system and 2 of the New York state university system. We were unable to obtain information for the University of Oregon, which reduces the number of universities to 59. As we explain below, the University of California, Berkeley is also excluded from the sample because we could not identify which of the UC system patents belonged to that campus. As such, the final dataset reflects patents assigned to 58 AAU universities. Accordingly, the final dataset reflects patents over time for 58 AAU universities.

To source the patent data for each university in the sample we searched the patent database maintained by Thomson Innovation using the name of each sample university; we then retrieved information on patent application and grant dates, the number of forward citations, and the list of inventors and assignees to construct the variables described above. The resulting dataset includes information on all 55,919 patents granted by the United States Patent and Trademark Office (USPTO) from 1969 through 2012 to a) single campus US universities that are AAU members (except the University of Oregon) and b) to all universities, including non-AAU members, of the system universities of California and New York.

To assign patents from the system universities to campuses we employ the patent Network Dataverse maintained by Harvard Business School which lists the location address of all inventors listed in patents granted by the USPTO. Based on this location information we measure the distance of each patent inventor to each of the system campuses, and assign the patent to the closest campus. In cases where the inventor(s) were located between multiple campuses we omit the

patent from the analysis (see Table 1 for details). This procedure eliminates 6,621 patents from the analysis and reveals that 358 patents were assigned to campuses of system universities that were not AAU members. Omitting these patents results in our final sample of 48,940 patents. These patents were granted from January 28, 1969 to December 25, 2012 (the corresponding application dates are March 29, 1957 to May 29, 2012).

For each sample patent, forward citations are measured as of December 2012. We collected information on campus incubators, including founding dates, from university websites, Lexis-Nexis and other news databases, and direct contacts with universities and their technology transfer offices.

Figure 1 shows the numbers of patents granted, licensing income, and the number of incubators established during each of our sample years.

--- Figure 1 about here ---

As seen in Figure 1, the last two decades have witnessed a secular increase in university patenting and associated licensing income. University incubators have been also been established with increasing frequency.

The number of patents per year increases steadily until 1999, stays at high levels with small yearly deviations from 2000 to 2009, and picks up again in 2010. Not shown in Figure 1, from 1969 to 1989 the sample universities were granted 282 patents per year, on average; the corresponding figure for the 1990–99 period is to 1,344. Since 2000 the AAU universities as a whole have patented 2,274 inventions per year. The establishment of incubators proceeds more unevenly but close to 80 percent (36 of the 47) started after 1999. Interestingly, this is also the period

in which patenting is becoming a university priority.[13] Purdue established the first university incubator in 1961, followed by Georgia Tech nearly two decades later in 1980. Also note that in support of the one-year patent lag we employ in the empirical specification, for the most part, spikes and downturns of licensing income in time *t* match with spikes and downturns in the rate of patenting in *t*-1 (see licensing income in 2007 and 2011 as examples)

Descriptive statistics are provided in Tables 1, 2, and 3. Table 1 presents the number of patents per university across the study period and the average licensing income per university from 1991 to 2012. The most patent-intensive campus is MIT, with its patents accounting for 8.4 percent of the sample patents. The University of Texas at Austin, Stanford, Cal Tech, and the University of Wisconsin round out the top five, followed by a group of mostly land-grand universities with more than 1,000 each. Note that the table underreports patenting at the University of California system of universities. Several campuses are located close to each other (e.g. UC Berkeley and UC San Francisco), and some UC system patents were excluded from the analysis because the inventor(s) were located equally near both campuses and we could not identify the home institution of those inventors.[14] If we include these patents and treat the UC system as a single university, UC is the most prolific patenting institution with more than 8,000 patents in the sample period. With regards to licensing income, New York University tops the list with on average $111 million per year, followed by Columbia University, Northwestern, the University of Wisconsin, and Stanford.

[13] Nine our sample universities did not have an incubator by the end of 2012: the University of Pennsylvania, the University of California–San Diego, Washington University in Saint Louis, University of Colorado, University of California–Santa Barbara, University of California–Irvine, Tulane University and Brandeis University.

[14] Previous works have opted to drop system observations altogether (Wong and Singh, 2010).

--- Table 1 about here ---

Table 2 summarizes the variables we use in the analysis. Our primary dependent variable, forward citations per year, is skewed, with a mode of zero: most university patents in our sample did not receive any forward citations. As indicated by the difference between the standard deviation (2.44) and the mean (1.36), there is significant variability in forward citations. In the year before the application date of the focal patent, our sample universities, submitted, on average, 52 patent applications (that were later granted patent rights) listing 3 inventors and 1 assignee. Most patents were listed under one 4-digit IPC code and had, on average, 16 and 22 patent and non-patent references, respectively. Note that the modal values of 0 both for PATENTREF and NONPATENTREF come mostly from early patents of the 1960s and the 1970s. More recent patents tend to have more extensive lists of backward references. Indeed, the differences in the backward references are strongly indicated by the large standard deviations of PATENTREF and NONPATENTREF compared to their mean values. Thirty percent of the patents were classified as biotech and thirty nine percent as information and communication technology.[15] Finally, more than 26 percent of the sample patents (13,039 of the 49,840) were applied for after the host campus established its incubator.

--- Table 2 about here ---

As seen in Table 3, the correlation coefficients of the variables used in the analysis are relatively weak which should help us to estimate the net effect of each of the independent variables on the value of university patents.

[15] To assign patents to technology areas we matched the IPC codes of the sample patents withe the lists of Biotech and ICT related IPC codes provided by the OECD.

--- Table 3 about here ---

6. RESULTS

6.1 Baseline estimates

We start with an OLS regression, reported as our baseline estimates in Table 4. For all the estimates we report robust standard errors clustered at the university level. The fit statistics at the bottom of Table 4 indicate that the OLS model has reasonable explanatory power, though it explains a rather limited portion of the observed variance. The multicollinearity index is somewhat inflated, above the threshold level of 30, yet well below the worrisome level of 100 (Belsley et al., 1980). Elevated condition indices could inflate the standard errors and subsequently impact inference. Nevertheless, the inferences in models we present as robustness checks, which have lower multicollinearity indices, and in the baseline models are almost identical, indicating that multicollinearity does not hamper our estimates materially.

To address endogeneity we use the Two-Stage Residual Inclusion (2SRI) method pioneered by Terza et al. (2008). In the first stage we regress the probability that university *i* establishes/maintains an academic incubator at time *t*, defined as the application date of the focal patent, as a function of the number of already established incubators at peer institutions and university-specific characteristics.[16] We present the first-stage regression in Appendix Table 1. As expected, the more peer institutions that have established an incubator previously, the higher the

[16] To populate the list of regressors for the first stage estimation we adopt the view that incubators and other auxiliary services towards commercialization are set in place chiefly as a means to expand the opportunity set of academics and others that have an inclination towards entrepreneurship (Fini et al., 2011; Mian, 1996). As such, we would expect universities to establish incubators when the on campus research has elevated commercial potential. Accordingly, because medical inventions tend to be more marketable than inventions from other disciplines (Powers, 2003), we include a dummy variable that takes the value of 1 if the university has a medical school and 0 otherwise. In the same vein, we include the EXPERIENCE variable to capture the intensity of innovation efforts on campus and a dummy variable that takes the value of 1 if the university is private and 0 otherwise as a means to account for the culture of universities and the overall attitude towards applied research (Friedman and Silberman, 2003).

chance the focal university will establish an incubator. In the second stage we include the residuals from the first stage in our baseline regression explaining licensing income. Model 2 of Table 4 presents these estimates. Also in support of our choice of instrumental variable, the residuals of the first stage are statistically significant in the second stage.[17]

--- Table 4 about here ---

The overall conclusions from the OLS and the 2SRI estimates agree. We find that the establishment of on campus incubators is followed by a reduction in patent quality. But, the 2SRI estimate on INCUBATOR is larger than the OLS estimate[18] which implies that the OLS estimate presents a lower bound on the (detrimental) effect of incubators on patent quality. In the remaining of the manuscript we refer only to the baseline estimates.

The baseline coefficient of INCUBATOR suggests that patents applied for after the establishment of an incubator receive 0.215 fewer forward citations per year. Besides the statistical significance, the size of that coefficient is also meaningful. To illustrate, if we evaluate the 0.215 figure at the mean value of the dependent variable, 1.36, as reported in Table 2, it suggests that the number of forward citations per year of the average patent decreases to 1.15—a 16 percent reduction. If evaluated at the median value, the reduction of forward citations per year exceeds 42 percent.

[17]Following Terza et al. (2008) we employ bootstrapped standard errors to account for the presence of the first-stage residual in the model of the second stage. In general, applications of the 2SRI method can be found in a number of areas including policy analysis (Beaudry and Allaoui, 2012) and strategic management (Berry, 2013). Cai et al. (2011) discuss in detail the (desired) asymptotic properties of the 2SRI method when, as in our case, the first stage is a probabilistic model.

[18] What may explain this difference is that universities may mistakenly think that incubators will lead to better patents. When they anticipate a future improvement in their innovative capabilities (e.g., they have just gotten some new grants or endowment funds, they have just hired some star professors, they have just built some new labs, etc.) - developments that, independently of an incubator, should give them better patents - they establish an incubator. Thus even though incubators have a detrimental effect, the fact that they are established under those circumstances makes this effect appear smaller.

What is going on? If resources, tangible and intangible, are constrained, then inputs that support activities related to the incubator are less valuable, on the margin, then inputs supporting other innovative activities on campus. For example, given that university-based firms are more successful when faculty founders are more actively involved (Fuller and Rothaermel, 2012) faculty have strong incentives to invest time on incubator-related issues (administrative work, recruiting personnel, meeting with potential tenants, etc.); this time would otherwise have been spent on research related to innovation, leading to a decline in the quality of that research. Incubator tenants may also be using equipment, laboratory facilities, student labor, and other resources that are not available for other campus activities. Our results suggest that these effects, ceteris paribus, must outweigh the positive spillovers between incubator and non-incubator activity usually described in the literature on academic incubators.

The results for the experience variables are particularly interesting. While the focal university's previous year experience in patenting has an unexpected negative and statistically significant effect on patent quality, its economic magnitude is tiny, suggesting that university experience has a limited impact on patent value. In unreported models we replace the one year experience lag with different lag structures including $t = 0$ and $t-3$ (strong correlations between the lags prompt us to not include all the lag structures simultaneously). In these models the results remained unchanged. This is a relevant observation because it reinforces our conclusion that the volume of recent patent activity of the focal university has a statistically significant positive but economically weak effect on patent quality. As such, it alleviates concerns that the intensification of patenting activities can come at the expense of patent quality (note that the values for the experience variables at $t = 0$ are similar to those $t = 1$, hence the lag structure essentially also captures potentially contemporary effects). What appears to matter more is the experience of universities in producing higher-quality patents. Patents coming from universities with previous high-quality

patents received 0.182 more forward citations than patents of universities with less experience in high quality patents.

Contrary to expectations, biotech patents receive less forward citations per year but in line with theory the opposite holds for ICT patents. The variables that capture the effects of collaboration suggest that patents with more inventors (but not with more assignees) tend to be more valuable. However, the negative sign of the interaction term implies that the relationship between number of inventors and assignees is subject to diminishing returns. Finally, the remaining control variables we use in the analysis imply that a) patent scope has a significant impact on patent value, b) an increased number of patent references is associated with more forward citations, and c) the number of non-patent references does not impact patent value. Not shown in Table 4, most of the university- and year-specific coefficients are statistically significant and this suggests that year to year differences as well as a time-invariant university features also matter for university patent quality.

To test the robustness of our baseline findings we perform a series of checks which are presented in Table 5.[19]

--- Table 5 about here ---

In section 3 we discussed how resource scarcity can drive the deteriorating effect of incubators on innovation quality. Models 1 and 2 of Table 5 test whether this theoretical mechanism is supported by empirical evidence. In model 1 we limit the analysis to the less research-endowed

[19] Besides the robustness checks we present here, we have performed additional tests which are available upon request. These tests include: (a) inclusion of student incubators when constructing the INCUBATOR variable, (b) defining only same state institutions as peers when defining the instrumental variable (c) drop from the analysis the ICT, BIOTECH and EXPERIENCE variables which have the highest Variance Inflation Factor among all variables (d) replace the 1 year lag for the patent-specific variables with a 5 year average, (e) run a robust regression to test the impact of the outliers and (f) include a variable indicating whether the focal university is single or multi-campus. In all these tests, the results are qualitatively equivalent to the baseline estimates and further reinforce our main conclusions.

universities in the sample (i.e. those whose average research budget in the last 5 years is below the median among the sample universities). In model 2 we limit the analysis to the most resource-endowed cohort of sample universities. In line with the resource-based argument we set forth in section 3 we find that the deteriorating effect of incubators on innovation quality is more pronounced among the less research-endowed universities. More specifically, the incubator coefficient for the more resource-endowed universities is −0.20, while the corresponding coefficient for the less resource - endowed schools is −0.25. Therefore, while the deteriorating incubator effect holds among all universities, it is 25 percent stronger for those universities with less resources.

Model 3 tests the sensitivity of our conclusions to the effective time needed for a given patent to accumulate citations. Because we measure citations per year we might discount the value of earlier patents as they might not have enough time to accumulate citations, while favoring older patents which have had longer to garner them. Following previous works (e.g Burke and Reitzig, 2007; Nemet, 2009) we construct the dependent variable for model 3 using only the citations accumulated within 5 years of the patent publication. The results are similar to those in the baseline estimates, though the coefficient of the INCUBATOR variable is now smaller.[20]

In model 4 we employ a negative binomial estimator to conduct the analysis instead of the OLS estimator we use for the baseline estimates. The two estimates yield qualitative similar results. As such, we conclude that the effects we reveal are not sensitive to the estimation technique.

[20] Because we measure citations through the end of 2012, the 5-year citation window is truncated for patents granted in later years. To test whether this truncation impacts our results we also run the baseline analysis in a sample including only patents granted up to 2008, thus giving all patents five years to accumulate citations. The estimates from this test are qualitatively similar to the estimates we present here.

The baseline estimates rely on the implicit assumption that the impact of incubators on patent quality takes place shortly after the establishment date of the incubator. Model 5 tests the sensitivity of our estimates to the possibility that the effective time needed before this impact materializes is not immediate. Specifically, we consider as "post-incubator" only patents that have been applied at least one year after the establishment date of the incubator. The estimates in model 5 are nearly identical to the estimates of the baseline model and reinforce our main conclusions.

6.2 Effects of Incubators on Licensing Income

As noted above, we base our analysis on the premise that patent forward citations are a meaningful measure of economic value, as is conventional in the innovation literature (Gambardella et al., 2008; Harhoff et al., 2003). Our expectation is formed, in large part, by the notion that "universities patent in order to license" (Thursby and Thursby, 2007) and the finding that patents increase the likelihood of licensing agreements (Elfenbein, 2007; Gans et al., 2008). Accordingly, we expect a) patented inventions to generate most of licensing income and b) more valuable patents to generate higher licensing income (Dechenaux et al., 2008).[21] However, unpatented inventions can also generate licensing income (Kotha et al., 2013) and, as we theorize, if the incubator effect extends to all university-based innovation efforts, including both patented and unpatented, we should observe such effect in licensing income changes.

Accordingly, as an additional check on the *overall* effect of incubators, we run a new set of tests looking at university licensing revenues, rather than patent quality, as an outcome variable.

[21] Note that licensing revenue per patent is driven by two factors, the probability that the patent will be licensed, and the amount of revenue going to those that are licensed. As Elfenbein (2007) points out, these drivers may have different sources (e.g., for the former, the reputation of the lead scientist, and for the latter, the capabilities of the university's technology transfer office).

Even if establishing an incubator has a negative effect on average patent quality, a few high-quality patents—"home runs"—could generate enough additional licensing revenue to justify their cost, including the direct and indirect costs of establishing and maintain the incubator. (Whether this is consistent with the university's scientific and educational mission is another question.) If there are not enough high-quality patents to compensate for the reduction in patent quality, then total licensing revenue will fall.

Specifically, we construct a second sample using the university as the unit of analysis and the university's total licensing revenue per year as the dependent variable. We obtain licensing income per university from 1991 to 2012 from the Association of University Technology Managers (AUTM).[22] We started with the same 58 AAU universities we analyze in the baseline estimates. But, because for system universities (University of California and the New York system) AUTM reports licensing income only for the system we follow previous works (Wong and Singh, 2010), and drop the system campuses from the analysis. Accordingly, the final dataset reflects licensing income over time for 51 AAU universities. The AUTM data are based on licenses matched to innovation disclosures, only some of which are patented, so this is not a specific measure of the licensing income derived from university patents, but a general measure of the financial returns to university innovation efforts.

Besides the incubator effect, we expect university features and characteristics of the patents that lead to licensing to also affect licensing income.[23] As such, we include in the analysis a number of variables that describe each focal university and its patents. We expect a one-year lag of

[22] The panel is unbalanced as not all universities report their licensing income for all years.

[23] While patenting is the typical means to generate licensing income (Thursby and Thursby, 2002), there are cases under which unpatented inventions also yield licensing income (Kotha et al., 2013). Our data source does not describe such unpatented inventions and hence we cannot include them in the analysis. This is a limitation of our work. A priori, though, we cannot approximate the scope of this limitation as the most comprehensive evidence on unpatented inventions leading to licensing comes only from one university (Kotha et al., 2013). This university is not

the dependent variable (*LAG*) to account for path dependencies that determine licensing income (Heisey and Adelman, 2011). To account for the experience of the Technology Transfer Office and its size we include a variable that measures it's age (*TTO_AGE*) and a variable that measures the number of employees (in full time equivalent) devoted to licensing (*TTO_SIZE*). Private and public universities may provide different royalty rates from licensing towards faculty and this may affect licensing income (Lach and Schankerman, 2008), so we include a dummy variable for private schools (*PRIVATE*). Finally, to account for the possibility that licensing income is a function of the volume of patent activity, we include the number of patents granted to the focal university in the previous year (*EXPERIENCE*).

As already introduced, with regards to patent-specific features, we expect more valuable patents that raise the cost of imitation to generate higher licensing income (Dechenaux et al., 2008). To capture this we include a forward-citations measure aggregated to the focal university, i.e., the average number of citations per year received by all university patents granted in year $t-1$, with t being the focal year (*FORWARD*). Following arguments discussed above we construct and include in the analysis two variables (*BIOTECH* and *ICT*) that measure the number of patents in year $t-1$ from those two industries.

We include additional university-specific variables similar to those used in the forward-citations models (all measured in the year prior to the focal year), such the average number of different four-digit International Patent Classification categories assigned to university patents (*SCOPE*) along with the average number of assignees for university patents and inventors granted (*ASSIGNEES*, *INVENTORS*). We also include a variable that measures the average number of

identified in the study in question, hence we are not aware on whether it is in our database. More importantly, we cannot know whether the patterns in that university are reflective of the population of universities, including those in our sample.

non-patent references (academic literature, government reports, and so on) included in the university patents (*NONPATENTREF*) and a variable that measures the average number of patents listed in the references list of the university patents (*PATENTREF*).

Finally, we include a set of university-specific and time-specific dummy variables to account for unobservable characteristics of particular universities that might influence their licensing income and for year-to-year fluctuations (Lach and Schankerman, 2008).

With regards to descriptive statistics of the new sample used to construct the models explaining yearly licensing income per university, the dependent variable has an average value of 18.74 million with a standard deviation of 51 million and the INCUBATOR variable takes the value of 1 for more than one third of the observations. Of the universities represented in our sample, about half are private (48 percent). The average university TTO is 20 years old and employing 7.6 FTEs for licensing. On average each university was granted 32 patents in the year preceding the focal year and the modal value was 10. Ten of those patents where related to biotechnology applications and more than 12 to ICT.

--- Table 6 about here ---

Table 6 presents the estimates from the models explaining yearly licensing revenue for the sample universities. Model 1 is the reference specification, model 2 is the instrumental variable model (exploiting the peers instrument described previously where, in this case, we model the probability that an incubator is established in a given year) and models 3 to 7 are robustness checks. The models have strong explanatory power but the underlying data exhibits high multicollinearity, which could lead to erroneous inference. As we explain later, the conclusions of model 6, with a significantly lower multicollinearity index agree with the conclusions of model 1; hence multicollinearity does not appear to come at the expense of incorrect inference.

The results largely corroborate our findings using forward citations as the dependent variable. As seen in Table 6, average licensing income falls after the establishment of an incubator, hence, again, a deteriorating effect. However, as we explain in footnote 20, we do not account for unpatented ideas that can generate licensing income. Hence, we treat these results with caution. Because the dependent variable is in logarithmic form and the independent variables in levels we can interpret the estimated coefficients as semi-elasticities. The INCUBATOR estimate of model 1 suggests that the establishment of an incubator is followed, on average, by a 14 percent decrease in licensing income. To illustrate the economic significance of the coefficient, we evaluate it at the median value of the dependent variable (not in log), 4.4 million: it suggests that licensing income decreases by more than $0.6 million per year. This is an important finding indicating that the effects we reveal in the baseline estimates presented in Table 4 are not specific to the variable of interest (forward citations) but reflect larger changes.

In line with previous works (Heisey and Adelman, 2011), we find that one-year lagged licensing income is a strong predictor of licensing income at time *t*. This finding likely emanates from the fact that licensing agreements are typically in effect for multiple years. Further, one additional biotechnology patent in the previous year increases licensing income by 1.1 percent. On the other hand, increased values of patent scope associate, somewhat surprisingly, with decreases in licensing income. The remaining patent-specific variables we include in the analysis do not have significant explanatory power. With regards to university-specific features, we do not observe a difference between public and private institutions but the experience of the TTO and its staff size dedicated to licensing, have a statistically significant but small correlation with increased licensing revenue. The volume of patent activity of the focal university in the previous year does not ex-

plain licensing income either. Not shown in Table 6, most of the university- and year-specific coefficients are also statistically significant; year to year differences and a time-invariant university features can also matter for licensing income.

The instrumental variable results presented in model 2 are similar to the reference estimates and the significance of the residuals indicates that the peer instrumental variable has desirable properties.

In the reference estimates we describe the patents granted in t-1 assuming that the bulk of the licensing income is derived from them. In model 3 we investigate the sensitivity of our results to that assumption; we replace the patent-specific variables (and the lagged dependent variable) at t-1 with corresponding variables for patents in t-2 (unreported results using a t-3 lag yield identical estimates). The main conclusions remain intact. Interestingly, the INCUBATOR coefficient in model 3 is larger than the INCUBATOR coefficient in the reference model.

The list of regressors includes forward citations to control for patent market value and for additional patent-specific variables (e.g. scope and size of inventors team) that capture remaining factors that can increase licensing income. However, the latter group of variables can also influence patent value (e.g. Czarnitzki et al., 2011; Sapsalis et al., 2006) leading, thus, to endogenous variables. Against this background, in model 4 the analysis omits patent-specific variables that can explain forward citations. The results indicate that the potential endogeneity in question does not hamper the estimates.[24]

In model 5 we omit from the specification the lagged dependent variable. The main conclusions side with the conclusions we derive from the reference estimates. However, the magnitude

[24] We reach identical conclusions when we omit only the forward citations variable.

of the INCUBATOR coefficient increases. A potential driver behind this finding is that the INCUBATOR variable is picking up effects captured by the one year lag. Unreported results, which are available upon request, where we include a one year and a two year lag in the analysis, support this proposition. In model 6 we omit all variables that inflate the multicollinearity condition index. Inference remains largely unchanged.

The incubator effect might be different in multi-campus universities where central decision making and knowledge flows may be different than single campus schools. To account for such possibility in model 7 we add a variable that takes the value of 1 if the focal university has more than one campus, 0 otherwise. We do not find evidence of such effect as the results are nearly identical to the baselines estimates and the single campus variable is not statistically significant.

7. DISCUSSION AND CONCLUSION

University incubators, like other technology business incubators, are generally seen as effective mechanisms for translating academic research into commercially useful innovations and value-adding start-up companies. Indeed, some incubators, like Georgia Tech's—the second-oldest among AAU universities—have an impressive record (Rothaermel and Thursby, 2005b) in spawning new ventures, contributing to innovation and local economic growth. But most of the existing literature on incubators looks at an incubator's outputs, not the change in the university's overall innovative performance before and after an incubator is established. Such an approach ignores the fact that the decision to establish an incubator is not made in isolation, but reflects an overall philosophical shift towards commercialization at the university in question.[25] Accordingly, even if incubators generate useful and commercializable knowledge, they may also compete with other university programs that also attempt to foster innovation and generate revenue.

[25] Our conversations with university commercialization personnel consistently emphasize this point.

Our work complements previous literature that demonstrates the positive contributions of incubators on innovation (e.g. Colombo and Delmastro, 2002; Kolympiris and Kalaitzandonakes, 2013; Markman et al., 2004) by suggesting that such contributions may come at the expense of other, equally valuable academic innovative activities. Specifically, we find that the establishment of a university incubator is followed by a decline in the average quality of the university's patents, controlling for patent-, university-, and time-specific characteristics. The results hold while also controlling for the potential endogeneity of the decision to establish an incubator. Along the same lines, we document a detrimental effect of incubators on university innovation efforts when we examine how overall university licensing income changes after the establishment of incubators.

To be clear, our results do not imply that incubators destroy value, as university incubators serve many purposes, educational as well as commercial.[26] This is a point worth emphasizing as ultimately, the net economic effect of incubators is the variable of interest. The presence of an incubator may attract particular kinds of faculty and students, enhance the prestige of the university, generate economic multiplier effects and benefit the community as a whole. Because we do not measure these other outcome variables, or capture positive spillovers more generally, we cannot quantify the net effects of university incubators on innovation and on economic value as a whole. However, much of the public discussion around incubators focuses on their specific im-

[26] An OECD handbook on incubators urges universities not to emphasize the educational aspects of their incubators, however. "[When universities are closely involved in the set-up of the incubator, there can be a conflict of views on the role of the incubator as a training tool (i.e. the view of education policy) and as a generator of high-potential start-ups (i.e. the view of business support policy). These approaches need to be reconciled, bearing in mind that a business incubation program that has a purely educational function is questionable and likely to produce poor value for money, though training and mentoring do play an important role in this policy. . . . When incubators are established within campuses, there is a danger that a wrong message about the contents of the program is transmitted to potentially interested participants. The incubator management will have to make it clear that training and teaching for tenant firms is of practical rather than academic nature" (OECD, 2010 pp 5).

pact on patenting, which generates licensing and other revenues. The decision to establish an incubator should thus be informed by large scale estimates of these specific effects. Our results suggest that university incubators may not generate net benefits for campus innovation. These are important findings for university administrators, policy makers, and remaining stakeholders who seek to promote innovation via the commercialization of academic research.

Our findings also have implications for innovation research. The literatures on incubators and academic patenting have, for the most part, developed independently, but our approach and results suggest grounds for integration. Further research can explore these links in greater depth. Another promising avenue for future research would be to examine more closely the specific mechanisms by which incubators affect university-based innovation, along the lines of Rothaermel and Thursby (2005a, b). Similarly, qualitative work can shed new light on the effect of academic entrepreneurs on the relationship between incubators and patent quality. More generally, a fruitful avenue for future work would be to use the university as the unit of analysis and try to determine how a given university should direct the marginal dollar to promote innovation (or other outputs)—to the incubator, the tech transfer office, laboratories, personnel, or academic programs? This question obviously has important implications for practice as well.

Our study has a number of limitations that can be addressed in future work. First, because we theorize that incubators may drain overall university resources, we do not distinguish between incubator-affiliated and non-incubator-affiliated patents. Making that distinction is not feasible in a large sample like ours; we would have had to investigate by hand all 48,940 patents, and the relevant information may not even be in the patent filing itself. University incubators do not maintain (or at least will not share) lists of patents they claim as incubator-related and, even so, it would be

hard to establish a consistent definition across incubators of what counts as incubator involvement. Still, smaller-sample, perhaps qualitative, research looking separately at incubator- and non-incubator-affiliated patents would be useful.

Second, our models using licensing revenue as the dependent variable do not distinguish patented and non-patented innovations, both of which can generate licensing income. In other words, while we know that total licensing revenue falls following the establishment of an incubator, and that average patent quality falls, we do not know if the reduction in licensing income comes specifically from reductions in licensing income accruing to patents. Follow-up works could investigate the impact of unpatented inventions on licensing revenue in depth.

Third, the lack of comprehensive data in the early years of the analysis prevents us from incorporating additional university-specific attributes in the analysis. Fourth, we focus exclusively on research-intensive universities and this may limit the generalizability of our results to remaining institutions that also establish incubators but boost their innovative efforts not so much via encouraging in house research but more so via alternative routes such as the promotion of student entrepreneurship. Fifth, we do not distinguish among different types of university incubators, e.g., treating life-sciences-oriented incubators differently from engineering-focused incubators. We do not have enough diversity in our incubator sample to handle these differences econometrically. However, we specifically excluded virtual and student-oriented incubators, so our incubator sample is fairly homogeneous in any case. Again, these all present opportunities for future work.

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REFERENCES

Acs ZJ, Anselin L, Varga A. 2002. Patents and innovation counts as measures of regional production of new knowledge. *Research Policy* **31**(7):1069-1085.

Aernoudt R. 2004. Incubators: tool for entrepreneurship? *Small Business Economics* **23**(2):127-135.

Barney JB. 1991. Firm resources and sustained competitive advantage. *Journal of Management* **17**(1):99-120.

Beaudry C, Allaoui S. 2012. Impact of public and private research funding on scientific production: The case of nanotechnology. *Research Policy* **41**(9):1589-1606.

Belsley DA, Kuh E, Welsch RE. 1980. *Regression diagnostics*. Wiley Online Library.

Berry H. 2013. When Do Firms Divest Foreign Operations? *Organization Science* **24**(1):246-261.

Bulut H, Moschini GC. 2009. US universities' net returns from patenting and licensing: A quantile regression analysis. *Economics of Innovation and New Technology* **18**(2):123-137.

Burke PF, Reitzig M. 2007. Measuring patent assessment quality—analyzing the degree and kind of (in) consistency in patent offices' decision making. *Research Policy* **36**(9):1404-1430.

Cai B, Small DS, Have TRT. 2011. Two-stage instrumental variable methods for estimating the causal odds ratio: Analysis of bias. *Statistics in medicine* **30**(15):1809-1824.

Campa JM, Kedia S. 2002. Explaining the diversification discount. *The Journal of Finance* **57**(4):1731-1762.

Carlson S. 2000. A 1000-Acre Incubator for Research and Business. In *The Chronicle of Higher Education*.

Colombo MG, Delmastro M. 2002. How effective are technology incubators?: Evidence from Italy. *Research Policy* **31**(7):1103-1122.

Colyvas J, Crow M, Gelijns A, Mazzoleni R, Nelson RR, Rosenberg N, Sampat BN. 2002. How do university inventions get into practice? *Management Science*:61-72.

Costas R, Zahedi Z, Wouters P. 2015. Do "altmetrics" correlate with citations? Extensive comparison of altmetric indicators with citations from a multidisciplinary perspective. *Journal of the Association for Information Science and Technology* **66**(10):2003-2019.

Czarnitzki D, Hussinger K, Schneider C. 2011. Commercializing academic research: the quality of faculty patenting. *Industrial and Corporate Change* **20**(5):1403-1437.

Dechenaux E, Goldfarb B, Shane S, Thursby M. 2008. Appropriability and commercialization: Evidence from MIT inventions. *Management Science* **54**(5):893-906.

Dutt N, Hawn O, Vidal E, Chatterji A, McGahan A, Mitchell W. 2013. The Co-Development of Markets and Firms: Exploring the Role of Incubators in Emerging Market Economies.

Elfenbein DW. 2007. Publications, patents, and the market for university inventions. *Journal of Economic Behavior & Organization* **63**(4):688-715.

Etzkowitz H. 1998. The norms of entrepreneurial science: cognitive effects of the new university–industry linkages. *Research Policy* **27**(8):823-833.

Etzkowitz H. 2002. *MIT and the Rise of Entrepreneurial Science*. Routledge: London.

Etzkowitz H, Webster A, Gebhardt C, Terra BRC. 2000. The future of the university and the university of the future: evolution of ivory tower to entrepreneurial paradigm. *Research Policy* **29**(2):313-330.

Finer B, Holberton P. 2002. Incubators: There and back. *Journal of Business Strategy* **23**(3):23-25.

Fini R, Grimaldi R, Santoni S, Sobrero M. 2011. Complements or substitutes? The role of universities and local context in supporting the creation of academic spin-offs. *Research Policy* **40**(8):1113-1127.

Fischer T, Leidinger J. 2014. Testing patent value indicators on directly observed patent value—An empirical analysis of Ocean Tomo patent auctions. *Research Policy* **43**:519-529.

Friedman J, Silberman J. 2003. University technology transfer: do incentives, management, and location matter? *The Journal of Technology Transfer* **28**(1):17-30.

Fuller AW, Rothaermel FT. 2012. When stars shine: the effects of faculty founders on new technology ventures. *Strategic Entrepreneurship Journal* **6**(3):220-235.
Gambardella A, Harhoff D, Verspagen B. 2008. The value of European patents. *European Management Review* **5**(2):69-84.
Gans JS, Hsu DH, Stern S. 2008. The Impact of Uncertainty Intellectual Property Rights on the Market for Ideas: Evidence from Patent Grant Delays. *Management Science* **54**(5):982-997.
Goldstein H, Renault C. 2004. Contributions of universities to regional economic development: A quasi-experimental approach. *Regional Studies* **38**(7):733-746.
Gonzalez Canche MS. 2014. Localized competition in the non-resident student market. *Economics of Education Review* **43**:21-35.
Guy S. 2013. U. of C. to open business incubator to spur innovation. In *Chicago Sun Times*: Chicago.
Harhoff D, Narin F, Scherer FM, Vopel K. 1999. Citation frequency and the value of patented inventions. *Review of Economics and Statistics* **81**(3):511-515.
Harhoff D, Scherer FM, Vopel K. 2003. Citations, family size, opposition and the value of patent rights. *Research Policy* **32**(8):1343-1363.
Heisey PW, Adelman SW. 2011. Research expenditures, technology transfer activity, and university licensing revenue. *The Journal of Technology Transfer* **36**(1):38-60.
Henderson R, Jaffe AB, Trajtenberg M. 1998. Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988. *Review of Economics and Statistics* **80**(1):119-127.
Hoenen S, Kolympiris C, Schoenmakers W, Kalaitzandonakes N. 2014. The diminishing signaling value of patents between early rounds of venture capital financing. *Research Policy* **43**(6):956-989.
Hsu DH, Ziedonis RH. 2013. Resources as dual sources of advantage: Implications for valuing entrepreneurial-firm patents. *Strategic Management Journal* **34**(7):761-781.
Igami M. 2013. Patent Statistics as Innovation Indicators? Hard Evidence.
Ke Q, Ferrara E, Radicchi F, Flammini A. 2015. Defining and identifying Sleeping Beauties in science. *Proceedings of the National Academy of Sciences* **112**(24):7426-7431.
Klein PG, Saidenberg MR. 2010. Organizational structure and the diversification discount: Evidence from commercial banking. *The Journal of Industrial Economics* **58**(1):127-155.
Kolympiris C, Kalaitzandonakes N. 2013. Geographic scope of proximity effects among small life sciences firms. *Small Business Economics* **40**:1059-1086.
Kotha R, George G, Srikanth K. 2013. Bridging the mutual knowledge gap: Coordination and the commercialization of university science. *Academy of Management Journal* **56**(2):498-524.
Lach S, Schankerman M. 2008. Incentives and invention in universities. *The RAND Journal of Economics* **39**(2):403-433.
Lanjouw JO, Schankerman M. 2004. Patent quality and research productivity: Measuring innovation with multiple indicators. *The Economic Journal* **114**(495):441-465.
Lerner J. 1994. The importance of patent scope: an empirical analysis. *The RAND Journal of Economics*:319-333.
Lockett A, Siegel D, Wright M, Ensley M. 2005. Resources, capabilities, risk capital and the creation of university spin-out companies. *Research Policy* **34**(7):1043-1057.
Mansfield E. 1991. Academic research and industrial innovation. *Research Policy* **20**(1):1-12.
Mansfield E. 1995. Academic research underlying industrial innovations: sources, characteristics, and financing. *Review of Economics and Statistics*:55-65.
Markman GD, Gianiodis PT, Phan PH, Balkin DB. 2004. Entrepreneurship from the Ivory tower: do incentive systems matter? *The Journal of Technology Transfer* **29**(3):353-364.
McMillen DP, Singell Jr LD, Waddell GR. 2007. Spatial competition and the price of college. *Economic Inquiry* **45**(4):817-833.
Meyer JW, Rowan B. 1977. Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology*:340-363.

Mian SA. 1996. Assessing value-added contributions of university technology business incubators to tenant firms. *Research Policy* **25**(3):325-335.
Montgomery CA, Wernerfelt B. 1988. Diversification, Ricardian rents, and Tobin's q. *The RAND Journal of Economics*:623-632.
Moser P, Ohmstedt J, Rhode PW. 2015. Patent Citations and the Size of the Inventive Step-Evidence from Hybrid Corn. National Bureau of Economic Research.
Mowery DC, Sampat BN, Ziedonis AA. 2002. Learning to patent: Institutional experience, learning, and the characteristics of US university patents after the Bayh-Dole Act, 1981-1992. *Management Science*:73-89.
Mowery DC, Ziedonis AA. 2002. Academic patent quality and quantity before and after the Bayh-Dole act in the United States. *Research Policy* **31**(3):399-418.
Nemet GF. 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. *Research Policy* **38**(5):700-709.
OECD. 2010. Innovation Policy Platform.
Owen-Smith J, Powell WW. 2001. To patent or not: Faculty decisions and institutional success at technology transfer. *The Journal of Technology Transfer* **26**(1-2):99-114.
Owen-Smith J, Powell WW. 2003. The expanding role of university patenting in the life sciences: assessing the importance of experience and connectivity. *Research Policy* **32**(9):1695-1711.
Park HD, Steensma HK. 2013. The Selection and Nurturing Effects of Corporate Investors on New Venture Innovativeness. *Strategic Entrepreneurship Journal* **7**(4):311-330.
Penrose E. 1959. *The Theory of the Growth of the Firm*. Oxford University Press: Blackwell.
Pisano G. 2006. Can science be a business? *Harvard Business Review* **10**:1-12.
Powell DE. 2013. The university-incubation connection: a series. *NBIA Review*. [December 16, 2013].
Powell WW, DiMaggio P. 1983. The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review* **48**(2):147-160.
Powers JB. 2003. Commercializing academic research: Resource effects on performance of university technology transfer. *The Journal of Higher Education* **74**(1):26-50.
Powers JB, McDougall PP. 2005. University start-up formation and technology licensing with firms that go public: a resource-based view of academic entrepreneurship. *Journal of Business Venturing* **20**(3):291-311.
Rey ED. 2001. Teaching versus research: a model of state university competition. *Journal of Urban Economics* **49**(2):356-373.
Rothaermel FT, Thursby M. 2005a. Incubator firm failure or graduation?: The role of university linkages. *Research Policy* **34**(7):1076-1090.
Rothaermel FT, Thursby M. 2005b. University–incubator firm knowledge flows: assessing their impact on incubator firm performance. *Research Policy* **34**(3):305-320.
Sampat BN, Mowery DC, Ziedonis AA. 2003. Changes in university patent quality after the Bayh–Dole act: a re-examination. *International Journal of Industrial Organization* **21**(9):1371-1390.
Sapsalis E, van Pottelsberghe de la Potterie B, Navon R. 2006. Academic versus industry patenting: An in-depth analysis of what determines patent value. *Research Policy* **35**(10):1631-1645.
Schumpeter JA. 1934. *The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle*.
Sneed KA, Johnson DK. 2009. Selling ideas: the determinants of patent value in an auction environment. *R&D Management* **39**(1):87-94.
Stensaker B, Norgård JD. 2001. Innovation and isomorphism: A case-study of university identity struggle 1969–1999. *Higher Education* **42**(4):473-492.
Swann P, Prevezer M. 1996. A comparison of the dynamics of industrial clustering in computing and biotechnology. *Research Policy* **25**(7):1139-1157.
Teece DJ, Pisano G, Shuen A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal* **18**(7):509-533.

Terza JV, Basu A, Rathouz PJ. 2008. Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling. *Journal of Health Economics* **27**(3):531-543.
Thursby JG, Jensen R, Thursby MC. 2001. Objectives, characteristics and outcomes of university licensing: A survey of major US universities. *The Journal of Technology Transfer* **26**(1-2):59-72.
Thursby JG, Thursby MC. 2002. Who is selling the ivory tower? Sources of growth in university licensing. *Management Science* **48**(1):90-104.
Thursby JG, Thursby MC. 2007. University licensing. *Oxford Review of Economic Policy* **23**(4):620-639.
Wang D, Song C, Barabási A-L. 2013. Quantifying long-term scientific impact. *Science* **342**(6154):127-132.
Wong PK, Singh A. 2010. University patenting activities and their link to the quantity and quality of scientific publications. *Scientometrics* **83**(1):271-294.
Youtie J, Shapira P. 2008. Building an innovation hub: A case study of the transformation of university roles in regional technological and economic development. *Research Policy* **37**(8):1188-1204.

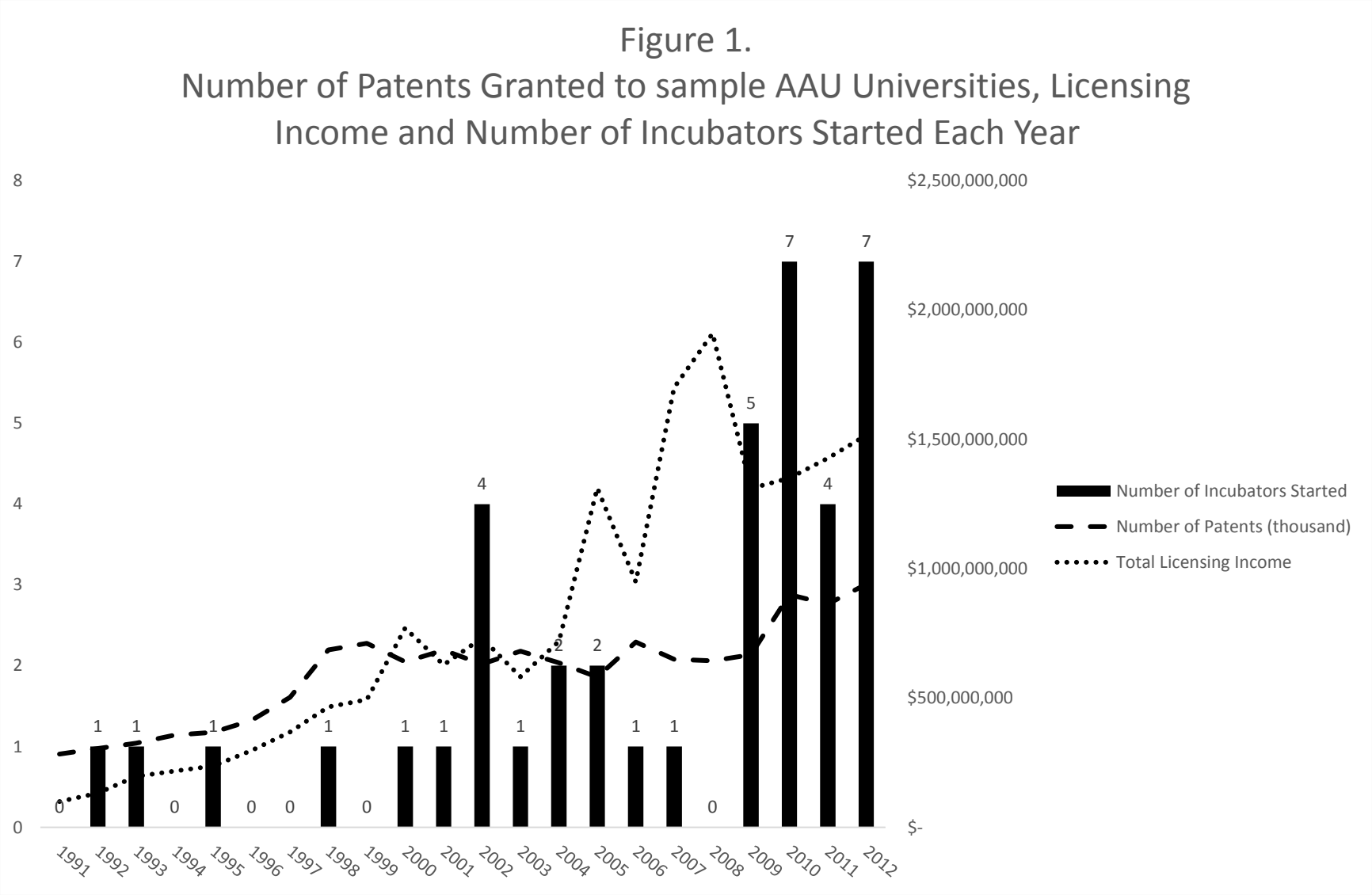
Figure 1.
Number of Patents Granted to sample AAU Universities, Licensing Income and Number of Incubators Started Each Year
8
7
6
5
4
3
2
1
0
$2,500,000,000
$2,000,000,000
$1,500,000,000
$1,000,000,000
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0 1 1 0 1 0 0 1 0 1 1 4 1 2 2 1 1 0 5 7 4 7
1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012
Number of Incubators Started
Number of Patents (thousand)
Total Licensing Income

Table 1. Patents, licensing and incubators from 1991 to 2012

University	Average licencing income per year (million)	Average number of patents per year	Incubator Establishment Year	University	Average licencing income per year (million)	Average number of patents per year	Incubator Establishment Year
New York University	111.02	39	2009	Texas A&M	6.73	23	2011
Columbia University	97.19	48	1995	Tulane University	6.41	6	no incubator
Northwestern University	81.36	27	2012	University of Chicago	6.23	43	2004
University of Wisconsin	55.43	83	1984	Cornell University	5.88	55	2002
Stanford University	50.76	93	2011	Vanderbilt	5.36	17	2002
University of Texas	50.51	103	1989	Case Western	5.15	15	2010
Massachusetts Institute of Technology	41.04	136	2012	Rutgers	5.15	25	2002
Emory University	40.09	17	no incubator	University of Virginia	4.82	15	2012
University of Washington	37.28	40	2012	Indiana University	4.07	10	2004
University of Minnesota	30.51	39	2006	University of Missouri	4.00	16	2009
Princeton University	27.81	22	2012	Purdue University	3.33	24	1961
University of Florida	26.66	52	2012	University of Pittsburgh	3.17	26	2002
University of Rochester	25.77	16	2010	University of Southern California	2.82	30	1998
Michigan State University	15.54	35	2012	Georgia Institute of Technology	2.50	39	1980
Harvard University	14.23	36	2010	University of Illinois	2.19	39	2001
University of Pennsylvania	12.18	46	no incubator	University of North Carolina	1.91	30	2013
Yale University	11.08	23	2007	University of Kansas	1.86	8	2010
University of Michigan	10.22	59	2011	Boston University	1.60	15	2005
University of Iowa	9.85	21	1984	Penn State	1.55	30	1993
University of Colorado	9.22	20	no incubator	Ohio State University	1.42	19	2005
Duke University	9.17	33	2009	Brown University	1.23	9	2009
Johns Hopkins University	8.65	66	2011	University of Maryland	1.01	34	1983
WUSTL	7.08	25	no incubator	University of Arizona	0.67	8	2003
Iowa State University	6.93	29	1987	Brandeis University	0.35	4	no incubator
Carnegie Mellon	6.80	18	2010	Rice University	0.23	13	2000

[a] The sample universities were also granted 6621 patents which we did not include in the analysis because they could not be assigned to separate campuses for the following reasons: The inventors of 3996 University of California System patents were located in between two or more campuses with the most common case being the University of California - Berkeley and the University of California - San Francisco. 502 University of California System patents had inventors in the Los Alamos Laboratory. 372 University of California System patents had inventors that were not residing in California (mostly foreign inventors). The inventor of 1 University of California System patent had a dual appointment with two University of California System universities. 1547 patents in the sample had more than 1 in-sample assignee. 203 patents assigned to the System of New York Universities had inventors not residing in the state of New York. Also note that 358 patents were assigned to system uiversities that were not AAU members. These patents are not included in the baseline analysis.

Table 2. Descriptive Statistics

	Variable Description	Variable Code	Number of Observations	Mean	Std Dev	Minimum	Maximum	Median	Mode
Dependent variable	(Number of times the focal patent has been cited by other patents since its grant date) / (December 31 2012 - grant date)	Forwardyear	48940	1.36	2.44	0.00	49.57	0.50	0.00
Continuous variables	Number of successful patent applications submitted by the focal university in the year before the application date of a given patent	Experience	49298	52.07	40.80	0.00	204.00	41.00	18.00
	Average number of forward citations per year gathered by patents used to construct the Experience variable	Forexperience	48406	1.60	0.93	0.00	22.72	1.44	0.00
	Number of non-patent references included in the list of references in the focal patent	Nonpatentref	48940	22.14	44.51	0.00	1045.00	7.00	0.00
	Number of patent references included in the list of references in the focal patent	Patentref	48940	15.75	31.63	0.00	837.00	7.00	0.00
	Number of inventors of the focal patent	Inventors	48940	2.70	1.62	0.00	22.00	1.00	2.00
	Number of assignees of the focal patent	Assignees	48940	1.11	0.35	0.00	6.00	1.00	1.00
	Number of IPC categories the focal patent belongs to	Scope	48888	2.24	1.54	1.00	18.00	2.00	1.00
Binary variables	Variable that takes the value of 1 if the focal patent has a biotechnology related IPC code and 0 otherwise	Biotech	48940	0.30	0.46				
	Variable that takes the value of 1 if the focal patent has an ICT related IPC code and 0 otherwise	ICT	48940	0.39	0.49				
	Variable that takes the value of 1 if the application date of the focal patent is after the opening date of the university incubator and 0 otherwise	Incubator	48940	0.26	0.44				

Table 3. Correlation Coefficients between Variables Used in the Analysis (excluding year and university - specific dummies)

	1	2	3	4	5	6	7	8	9	10	11	12
1. Forwardyear	1.000											
2. Incubator	-0.056	1.000										
3. Experience	0.069	0.043	1.000									
4. Forexperience	0.187	-0.114	0.310	1.000								
5. Biotech	-0.100	-0.005	-0.011	0.023	1.000							
6. ICT	0.098	-0.027	0.089	0.063	-0.135	1.000						
7. Nonpatentref	0.012	0.054	0.051	0.005	0.250	-0.061	1.000					
8. Patentref	0.095	0.047	0.088	0.011	-0.041	0.001	0.481	1.000				
9. Inventors	0.058	0.020	0.108	0.064	0.054	-0.001	0.126	0.113	1.000			
10. Assignees	-0.009	0.008	0.013	0.004	0.085	-0.047	0.113	0.074	0.311	1.000		
11. Inventors * Assignees	0.028	0.011	0.071	0.037	0.079	-0.027	0.133	0.103	0.826	0.711	1.000	
12. Scope	0.052	-0.009	0.035	0.093	0.368	0.062	0.184	0.080	0.130	0.076	0.123	1.000

Table 4. Baseline Estimates. The dependent variable is the number of forward citations per year (unit of analysis is the patent)

Variables / Model	1. OLS estimation		2. Two-stage residual inclusion estimation [a]	
Intercept	**0.152**		**0.374**	
	(0.217)		(0.124)	
Incubator	**-0.215**	***	**-0.432**	***
	(0.045)		(0.049)	
Number of patents in t-1	**-0.002**	**	**-0.002**	***
	(0.001)		(0.001)	
Forward citations of patents granted in t-1	**0.182**	***	**0.182**	***
	(0.028)		(0.021)	
Biotech	**-0.662**	***	**-0.665**	***
	(0.061)		(0.024)	
ICT	**0.398**	***	**0.398**	***
	(0.051)		(0.023)	
Nonpatentref	**0.000**		**0.000**	
	(0.001)		(0.000)	
Patentref	**0.008**	***	**0.008**	***
	(0.001)		(0.001)	
Inventors	**0.139**	***	**0.140**	***
	(0.028)		(0.022)	
Assignees	**0.026**		**0.029**	
	(0.145)		(0.062)	
Inventors * Assignees	**-0.041**	**	**-0.042**	***
	(0.019)		(0.015)	
Scope	**0.088**	***	**0.087**	***
	(0.027)		(0.009)	
Residual of first stage [a]			**0.059**	***
			(0.010)	
Year Dummies Included	YES		YES	
University Dummies Included	YES		YES	
R^2	0.112		0.113	
Adjusted R^2	0.111		0.111	
Multicollinearity Condition Index	38.329		38.332	
Number of Observations	48058		48058	

*** .01 significance, ** .05 significance, * .10 significance

Note: For model 1 robust standard errors, adjusted for heteroskedasticity and clustered by university, are reported in parentheses. For model 2 the standard errors are calculated using the bootstrap method

[a] The estimates of the first stage are presented in Appendix Table 1

Table 5. Robustness Checks of baseline estimates

Variables / Model	1. Conduct the baseline analysis only for universities whose yearly average research budget is below the median budget of the sample universities		2. Conduct the baseline analysis only for universities whose yearly average research budget is above the median budget of the sample universities		3. Conduct the baseline analysis using citations accumulated within 5 years from the patent publication date to construct the dependent variable (citations per year).		4. Estimate the baseline specification using a negative binomial estimator			5. Considering as post-incubator patents applied after 365 days from incubator's founding date	
	Estimate		Estimate		Estimate		Estimate	Marginal Effects		Estimate	
Intercept	**-0.027**		**0.231**		**-0.095**		**-0.547**			**0.145**	
	(0.504)		(0.195)		(0.093)		(0.082)			(0.217)	
Incubator	**-0.253**	***	**-0.203**	***	**-0.073**	***	**-0.241**	**-0.263**	***	**-0.210**	***
	(0.077)		(0.044)		(0.024)		(0.032)			(0.047)	
Number of patents in t-1	**-0.003**	*	**-0.002**	*	**0.001**	*	**-0.003**	**-0.003**	***	**-0.002**	**
	(0.002)		(0.001)		(0.000)		(0.000)			(0.001)	
Forward citations of patents granted in t-1	**0.147**	***	**0.214**	***	**0.051**	***	**0.110**	**0.126**	***	**0.183**	***
	(0.036)		(0.040)		(0.008)		(0.010)			(0.028)	
Biotech	**-0.497**	***	**-0.750**	***	**-0.217**	***	**-0.521**	**-0.546**	***	**-0.662**	***
	(0.076)		(0.079)		(0.019)		(0.020)			(0.061)	
ICT	**0.376**	***	**0.408**	***	**0.152**	***	**0.272**	**0.322**	***	**0.398**	***
	(0.067)		(0.071)		(0.016)		(0.015)			(0.051)	
Nonpatentref	**0.001**		**-0.001**		**0.001**	*	**0.000**	**0.000**		**0.000**	
	(0.001)		(0.001)		(0.000)		(0.000)			(0.001)	
Patentref	**0.009**	**	**0.008**	***	**0.005**	***	**0.006**	**0.007**	***	**0.008**	***
	(0.004)		(0.001)		(0.001)		(0.000)			(0.001)	
Inventors	**0.159**	**	**0.132**	***	**0.053**	***	**0.081**	**0.093**	***	**0.138**	***
	(0.071)		(0.035)		(0.009)		(0.012)			(0.028)	
Assignees	**0.323**		**-0.131**		**0.059**		**0.034**	**0.039**		**0.025**	
	(0.396)		(0.105)		(0.065)		(0.046)			(0.145)	
Inventors * Assignees	**-0.069**		**-0.029**		**-0.021**	***	**-0.027**	**-0.031**	***	**-0.041**	**
	(0.065)		(0.020)		(0.008)		(0.009)			(0.019)	
Scope	**0.031**		**0.123**	***	**0.012**	*	**0.045**	**0.052**	***	**0.088**	***
	(0.027)		(0.037)		(0.007)		(0.005)			(0.027)	
Year Dummies Included	YES		YES		YES		YES			YES	
University Dummies Included	YES		YES		YES		YES			YES	
R^2 (pseudo when applicable)	0.115		0.115		0.146		0.063			0.112	
Adjusted R^2 (pseudo when applicable)	0.112		0.113		0.145		0.062			0.111	
Multicollinearity Condition Index	42.567		40.467		38.329		38.329			38.295	
Number of Observations	18090		29968		48058		48058			48058	

*** .01 significance, ** .05 significance, * .10 significance

Note: Robust standard errors, adjusted for heteroskedasticityand clustered by university, are reported in parentheses.

Table 6. Estimates when the dependent variable is the logarithm of yearly university licensing income (the unit of analysis is the university)

Variables / Model	1. OLS estimation	2. Two-stage residual inclusion estimation [a]	3. Replace the 1 year lag structure of Model 1 with a 2 year lag structure	4. Omit from Model 1 variables that can drive patent value in the baseline analysis	5. Omit lagged dependent variable from Model 1	6. Omit variables that inflate the multicollinearity condition index from Model 1	7. Add a variable indicating whether the focal university has more than one campus
Intercept	**3.713** ***	**3.851** ***	**5.311** ***	**3.070** ***	**16.786** ***	**2.087** ***	**3.823** ***
	(0.843)	(0.782)	(0.957)	(0.664)	(1.079)	(0.392)	(0.894)
Incubator	**-0.140** **	**-0.325** **	**-0.271** **	**-0.133** **	**-0.613** **	**-0.083** **	**-0.132** *
	(0.063)	(0.148)	(0.108)	(0.060)	(0.269)	(0.037)	(0.067)
Number of patents in t-1	**-0.002**	**-0.001**	**-0.007**	**0.003**	**0.000**		**-0.002**
	(0.004)	(0.004)	(0.005)	(0.002)	(0.010)		(0.004)
Technology tranfer office age	**0.000** **	**0.000**	**0.000** ***	**0.000** **	**0.001** ***	**0.000** ***	**0.000** **
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Technology tranfer office size	**0.011** ***	**0.011** ***	**0.015** ***	**0.011** ***	**0.054** ***	**0.009** ***	**0.011** ***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.010)	(0.003)	(0.003)
Licensing income in t-1	**0.787** ***	**0.784** ***	**0.685** ***	**0.806** ***		**0.882** ***	**0.788** ***
	(0.038)	(0.034)	(0.049)	(0.042)		(0.022)	(0.038)
Average number of cumulative forward citations received by university patents granted in t-1	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000** **	**0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average number of non-patent references of university patents granted in t-1	**-0.002**	**-0.002**	**-0.002**		**-0.001**	**0.001**	**-0.002**
	(0.002)	(0.002)	(0.003)		(0.004)	(0.002)	(0.002)
Average number of patent references of university patents granted in t-1	**0.002**	**0.002**	**-0.002**		**0.003**	**0.000**	**0.002**
	(0.004)	(0.003)	(0.007)		(0.007)	(0.004)	(0.004)
Average number of inventors in university patents granted in t-1	**-0.023**	**-0.025**	**-0.099**		**-0.243**	**-0.029**	**-0.021**
	(0.048)	(0.059)	(0.065)		(0.202)	(0.032)	(0.048)
Average number of assignees for university patents granted in t-1	**-0.014**	**-0.010**	**0.325**		**0.218**	**-0.087**	**-0.022**
	(0.279)	(0.245)	(0.269)		(0.577)	(0.212)	(0.281)
Biotech	**0.011** **	**0.012** **	**0.012** *		**0.026** **		**0.011** **
	(0.005)	(0.005)	-0.006		(0.011)		(0.005)
ICT	**0.002**	**0.002**	**0.012** **		**0.002**		**0.003**
	(0.005)	(0.005)	-0.006		(0.013)		(0.005)
Average scope of university patents in t-1	**-0.109** ***	**-0.107** **	**-0.061**		**-0.243** **	**-0.031**	**-0.109** ***
	(0.032)	(0.052)	-0.080		(0.097)	(0.029)	(0.032)
Private	**0.002**	**-0.048**	**-0.033**	**-0.037**	**-0.581**		**-0.020**
	(0.162)	(0.100)	-0.242	(0.176)	(0.774)		(0.189)
Single campus							**-0.105**
							(0.175)
Residual of first stage [a]		**0.080** ***					
		(0.019)					
Year Dummies Included	YES	YES	YES	YES	YES	NO	YES
University Dummies Included	YES	YES	YES	YES	YES	NO	YES
R^2	0.886	0.886	0.841	0.884	0.703	0.873	0.8859
Adjusted R^2	0.876	0.876	0.826	0.874	0.678	0.872	0.875
Multicollinearity Condition Index	102.013	103.266	102.272	62.564	67.341	49.582	109.096
Number of Observations	908	908	861	913	937	908	908

*** .01 significance, ** .05 significance, * .10 significance

Note: For model 1,3,4,5 and 6 robust standard errors, adjusted for heteroskedasticity and clustered by university, are reported in parentheses. For model 2 the standard errors are calculated using the bootstrap method

[a] The estimates of the first stage are presented in Appendix Table 1

Appendix Table 1. First stage of two stage residual inclusion estimation. The dependent variable is the probability of a given university having established an incubator at a given time

	Estimates for baseline specification presented in Table 4 (dependent variable in the second stage is the forward citations per patent)			Estimates for specification presented in Table 6 (dependent variable in the second stage is the yearly licensing income per university)		
Variables	**Estimates**		**Marginal Effects**	**Estimates**		**Marginal Effects**
Intercept	**-0.662**			**0.090**		
	(0.616)			(0.229)		
Number of competing universities that had established an incubator previously	**0.627**	**	**0.070**	**0.428**	***	**0.088**
	(0.269)			(0.074)		
Experience	**0.000**		**0.000**	**0.006**	***	**0.001**
	(0.003)			(0.001)		
Variable that takes the value of 1 if the university is private, 0 otherwise	**-3.168**	**	**-0.384**	**-1.340**	***	**-0.268**
	(1.326)			(0.219)		
Variable that takes the value of 1 if the university has a medical school, 0 otherwise	**-0.867**		**-0.108**	**-1.551**	***	**-0.347**
	(0.939)			(0.223)		
Year Dummies Included	YES			YES		
University Dummies Included	YES			YES		
Pseudo R^2	0.366			0.286		
Adjusted R^2	0.364			0.230		
Wald test of overall model significance	10814.710	***		226.880	***	
Multicollinearity Condition Index	8.471			7.871		
Number of Observations	48940			1021		

*** .01 significance, ** .05 significance, * .10 significance

Note: Robust standard errors, adjusted for heteroskedasticity and clustered by university, are reported in parentheses.