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Article

Variation in patent impact by organization type: An investigation of government, university, and corporate patents

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Abstract

This article investigates whether patents assigned to different types of organizations—firms, universities, and government research agencies—vary with regards to their effect on subsequent technological change. We find the organization type to which a patent is assigned to have significant and robust effects on the number of times a patent is cited and its generality. More precisely, we find that university patents are cited more often than corporate patents and that both university and government patents are more general than corporate ones. Additionally, university and governments patents are more likely than corporate patents to be both highly cited and highly general. The finding that university patents have a particularly deep and wide impact on subsequent technological change suggests that policies that attempt to use universities as engines for advancing technological innovation may hold promise.

Key words: innovation; general purpose technology; university; government; research agencies; patents.

1. Introduction

Individual technological innovations vary dramatically in terms of their effects on subsequent technological progress. Certain innovations such as Cohen and Boyer's 'Process for producing biologically functional molecular chimeras' (US4237224) have demonstrated enormous capacity for spurring subsequent scientific and technological progress (Azagra-Caro et al. 2017; Feldman and Yoon 2012). Others such as a 'method of scoring a bowling game' (US6142880) have yielded no such bounty. Plainly, a society would prefer that a higher proportion of their innovations be of the former type. Thus, the identification of reliable determinants of high-impact technological innovations would appear a worthwhile endeavor. This article considers whether the type of organization that develops an innovation constitutes one such determinant. More precisely, in this article, we test whether the technological innovations developed by three types of organization—firms, universities, and government research agencies—vary in regard to their effect on subsequent technological progress.

The innovation-generating effects of Cohen and Boyer's contribution were both large and wide reaching.[1] In the parlance of patent citation analysis, the innovation was both *important* and *general*. In the investigation to follow, we consider the effect of organization type on these two dimensions. Importance refers to how frequently a technology is deemed to be critical to subsequent technological change.[2] It is measured as the number of citations a patent receives from future patents.[3] Generality refers to the technological breadth of a technology's impact on subsequent innovation. It is measured using the Herfindahl–Hirschman Index of the International Patent Classification (IPC) codes of patent's forward citations. In the present investigation, we compare a randomly-drawn sample of patents developed by US firms, universities, and government research agencies to determine whether these dimensions reliably vary based on organization type.

To preview our results, we find that patents assigned to universities are more important than those assigned to firms. That is, university patents are, on average and after controlling for other variables, cited more often than corporate ones. This finding is consistent with those of other scholars (Bacchiocchi and Montobbio 2009; Trajtenberg et al. 1997). We also find that patents assigned to universities and government research agencies are significantly more general than those assigned to firms. In other words, university and government patents affect subsequent technological change in a broader range of technological sectors than corporate patents. While theoretical arguments have been offered supporting the contention that universities and governments may have a comparative advantage vis-à-vis firms in developing general technologies, to our knowledge, ours is the first large sample empirical investigation of these claims. Finally, we define a subset of patents that are both highly and broadly cited. We find that both universities and government research agencies are significantly more likely to develop these high-impact innovations than are firms. The empirical finding that universities and government research agencies are more likely than firms to produce highly- and widely-cited patents is novel. All of these findings are robust to model selection, the introduction to control variables, the sample used, and the utilization of an alternative proxy for generality.

This study is motivated by the well-documented relationships between the importance and generality of patented innovations and economic outcomes. The remainder of this section briefly describes these relationships.

To justify the study of the relative technological importance of patents developed by different organization types, one only need consider the extent of heterogeneity in patent importance and the positive economic and technological correlates of importance. The abundance of patents issued for trivial or incremental inventions is well documented.[4] This practice may be becoming more common (OECD 2011; Schmid and Wang 2017). In contest, other patented innovations have been shown to drive technological progress for years or decades (Feldman and Yoon 2012). The observed variation in the importance of patented innovations is correlated with metrics of a patent's technological and economic impact. For example, forward citations (this study's measure of importance) have been shown to correlate with expert perception regarding the technological contribution of a given patent (Albert et al. 1991). Forward citations have also been shown to relate positively to the market value of a patent (Chen and Chang 2010; Lanjouw and Schankerman 2004; Odasso et al. 2015). Thus, scholars concerned with the identification of the determinants of radical technological change or the process of translating invention into economic outcomes should be interested in determining whether certain types of organizations tend to disproportionality develop highly-cited patents.

The study of variation in the generality of innovations is motivated by the role that technological generality is thought to play in driving widespread technological advancement and economic growth. The general purpose technology (GPT) literature is the primary literature describing the relationship between the generality of a technology and its effect on subsequent technological innovation and growth. This literature describes the process of technological innovation as one that occurs in waves (Youtie et al. 2008: 316).[5] According to the GPT framework, a wave of innovation is initiated when a GPT emerges and instigates a multi-sector surge of downstream innovation. Bresnahan and Trajtenberg (1995: 83) describe the catalytic role of GPTs on widespread technological change stating, 'Whole eras of technical progress and economic growth appear to be driven by a few "General Purpose Technologies" (GPT's).'

Indeed, it is this purported contribution to accelerating widespread technological change that explains GPTs proposed role in driving economic growth. Bresnahan and Trajtenberg (1995) argue that because GPTs act as 'prime movers' for investment in complimentary innovations, they play an oversized role in determining economic growth rates (Bresnahan and Trajtenberg 1995: 84). While scholars differ in terms of the proposed model characteristics, many other studies have come to a similar conclusion regarding the centrality of GPTs to determining growth trajectories (Aghion and Howitt 1998; Helpman and Trajtenberg 1994, 1996).

The study of organization-specific variation in the impact of innovative outputs also has policy relevance. All of the organization types examined here depend, to some degree, on public resources. Local and national governments subsidize ostensibly-innovative firms in the form of, *inter alia*, direct investment inducements, research and development tax credits, and tax deferments. Government research labs are completely dependent on public funding. Universities depend on grants, subsidies, and preferential tax status. The justification of directing public resources to these organizations is often based on the expectation that the impact of a funded innovation will extend beyond the initial resource transfer. That is, government spending on innovation is partially justified based on the expectation that funded innovations will spawn future innovation. Thus, assuming policymakers seek correspondence between the stated objectives of their policies and policy outcomes, the efficacy with which distinct organization types spawn subsequent innovation is of direct relevance.

The remainder of this article is organized as follows. Section 2 reviews existing scholarship on the character of innovations produced by universities and government research agencies. From this literature, a series of hypotheses regarding the character of university, government, and firm patents are extracted. Section 3 describes the data, measurement, and modeling strategy that are used to test these hypotheses. In Section 4, we present the results. Section 5 concludes.

2. Literature and hypotheses

In the analysis to follow, we test six hypotheses. These hypotheses are derived from the existing theoretical and empirical literature on the comparative advantages of the three organization types considered here. The existing literature predicts that patents developed by universities and governments will be both more important and more general than those developed by firms. The rationale for these predictions is elaborated below.

2.1 University patents

A wealth of theoretical and empirical scholarship contends that university-developed patents will, on average, differ from those developed by firms. In regard to the characteristics under consideration here, patents developed by universities are argued to be particularly instrumental to subsequent technological progress and wide reaching in their technological influence. In the parlance of patent citation analysis, university-developed patents, when compared to those developed by firms, are argued to be important (highly cited) and general (draw their forward citations from a diverse set of technology classes).

Early, theoretical support for these claims traces to the work of Nelson (1959). While his focus is on explaining why the private sector will tend to supply basic research at a level below the social optimum, his reasoning can be applied to the development of patented inventions. Because innovation is cumulative, patents for which the underlying research is situated toward the basic end of the basic-applied research spectrum have the potential to be more important to subsequent innovation and spawn innovation in a wide range of technological sectors.

Nelson's reasoning uses the marginal analysis that is characteristic of welfare economics.[6] He begins by observing that the returns to basic research will be widely distributed across applications, space, and time. It is thus unlikely that any given firm will be able to fully appropriate the social returns to an investment in basic research. Universities, in contrast to firms, are not purely profit-driven. Consequently, the appropriation problem faced by universities is less severe than for firms. Thus, according to Nelson, the comparative advantage of universities 'lies in basic research' (Nelson 1959: 306).

Nelson goes on to argue that universities' comparative advantage in the conduct of basic research is extended by two additional factors: patent law and the short time horizons used by firms. Patent law exacerbates the appropriation problem associated with the returns to basic research. The output of basic research, in that is consists largely of 'natural "laws" and facts', is unlikely to be patentable (Nelson 1959: 302). Firms, precluded from using the predominant mechanism for monetizing the outcome of their research, will tend to forego investment in basic research. Nelson also argues that firms will prefer applied research to basic research due to the long lead times associated with making fundamental scientific discoveries. Nelson explains that, 'firms much concerned with short-run survival, little concerned with profits many years from now' will use higher time discount rates for basic research investments than are socially optimal (Nelson 1959: 304).

More recently, Rosell and Agrawal (2009) have provided an additional explanation for universities' proposed comparative advantage in the development of general technologies. The authors explain that firms face pressure to narrow the diversity of the prior art used, and cited in their patent documents, due to what Heller (1998) deems the anticommons. That is, firms will conduct research, and draft their patent applications, with an eye toward minimizing exposure to the myriad, possibly overlapping, claims of other patents. Universities, in contrast, are partially insulted from the tragedy of the anticommons due a legal exception that allows for patent infringement in cases of experimental use. Besides the experimental use exception, Rosell and Agrawal explain that university researchers will, relative to firms, select their research projects and prior art based on scientific merit. By selecting research based on scientific merit, and only considering patenting after the fact, university researchers avoid the *ex-ante* narrowing of scientific scope associated with the anticommons.

Finally, universities' purported relative advantage in developing GPTs is given additional theoretical support from the markets for technology framework (Bresnahan and Gambardella 1998). This framework contends that for special purpose innovations, vertical integration is optimal while for general purpose innovations, the separation of upstream and downstream processes (i.e. disintegration) is preferred. Within this framework, universities are particularly well positioned to specialize in GPTs because they tend not to control downstream assets and thus will not be burdened by disintegration costs (Barirani et al. 2017). Firms, in contrast, will tend to be more vertically integrated and, thus, relatively well-positioned to take advantage of special purpose innovations.

Empirical evidence generally supports the contention that university patents are particularly likely to be cited by subsequent patents and that these citations will tend to come from a wide range of technology groups. Using similar proxies to those used here, Trajtenberg et al. (1997) find that compared to a control sample of corporate patents, university patents were, on average, more highly cited and more general. While they do not look at generality, Bacchiocchi and Montobbio (2009) also find that university patents receive a higher number of citations. The authors also find that university patents are more likely to have received at least one citation. These results do not appear to depend on jurisdiction; Trajtenberg et al.'s finding uses USPTO patents, whereas Bacchiocchi and Montobbio (2009) use data from the European Patent Office.

Considering the theoretical arguments summarized above and the observation that university patents, from various jurisdictions, tend to be more highly cited and general than corporate patents, it is possible to formulate the following testable claims.

Hypothesis 1: University patents will receive more citations than otherwise comparable corporate patents.

Hypothesis 2: University patents will be more general than otherwise comparable corporate patents.

2.2 Government patents

The literature on the character of patents produced by government agencies is less well developed than that focusing on universities. Ruttan provides the theoretical framework from which this study's hypotheses regarding government patents are derived. Ruttan (2001, 2006a,b) argues that governments have been responsible for the development of a disproportionately large proportion of GPTs. In making this claim, Ruttan traces the historical process by which important GPTs—certain early mass production processes, nuclear power, semiconductors, the Internet, and others—were developed. In each case, Ruttan finds that the US government played an important role not merely in funding a given technology's underlying basic research, but in the development of the technology itself. According to Ruttan, the outsized role of the government in the development of these technologies does not owe to mere historical accident or the government's ability to correctly select emerging GPTs. Rather, the government has played an important role in the development of GPTs because GPTs are characterized by two traits that deter private investment.

First, the returns to GPTs are highly dispersed across industries making their capture by a single firm unlikely. If firms are unlikely to appropriate the full returns to their investment, private investment will likely be below what is socially desirable. In such cases, the successful introduction of a GPT may depend on government intervention. Second, Ruttan argues that the long development cycles typical of GPTs often exceed the time horizons used by firms. Ruttan notes that the development of GPTs often takes decades and doubts that firms will have the 'patient capital' necessary to make such long-term investments (Ruttan 2006b: 177). In essence, the high relative generality of government innovations owes to the government's comparative advantage vis-à-vis firms in providing public goods and making long-term investments.

A careful reader will have noticed that the reasoning underlying both of Ruttan's claims is analogous to that offered by Nelson (1959) and Rosell and Agrawal (2009). First, Ruttan's claim regarding the appropriation problem associated with GPT parallels the reasoning used by Nelson to describe the market failure associated with basic research. Second, Ruttan's claim regarding the role of time horizons is similar to Rosell and Agrawal's claim regarding the discount rates used by firms. Ruttan's contribution is to apply these traits to government-funded GPTs and describe their impact on the historical role played by the government in the development of these technologies.

The empirical literature on government-assigned patents is scant. Bacchiocchi and Montobbio (2009) find that patents assigned to government agencies accumulate more citations than a control group of corporate patents. While Drivas and Economidou (2013) do not look at government-assigned patents, they find circumstantial support for the large sample validity for the claims of Ruttan. In particular, the authors use USPTO data to find that patents developed using government funding were, on average, more basic than those that did not receive public support. Finally, Schmid (2017a) finds that in contrast to the expectation of prevailing theory, military patents diffuse at a rate that is not statistically disguisable from otherwise similar nonmilitary patents. That is, despite the significant barriers to diffusion—export controls, the classification system, and a static ecosystem of firms—that exist within the military technology innovation system, military technology patents are cited by other patents at a rate that is comparable to civilian technologies. Schmid suggests that this counterintuitive finding might be driven by the logic proposed by Ruttan. That is, because the government often funds military technologies, these technologies might be disproportionately general. This generality effect may counteract the effect of the barriers that segregate the military innovation system from the civilian one. This proposed explanatory mechanism, however, is left untested. Indeed, we do not know of any previous studies that have compared the generality of government-assigned patent to those developed by other types of assignees.

Based on Ruttan's argument, and the admittedly scant empirical evidence, we extract the following testable claims regarding government patents.

Hypothesis 3: Government patents will receive more citations than otherwise comparable corporate patents.

Hypothesis 4: Government patents will be more general than otherwise comparable corporate patents.

2.3 Highly- and widely-cited patents

The preceding discussion can be used to generate two final hypotheses regarding patents that are both highly *and* widely cited. If universities and governments are argued to have a comparative advantage in the development of important and general patents, these types of organizations may also be more likely to produce individual patents characterized by both high importance and high generality.[7] To our knowledge, these claims have yet to be tested empirically.

Hypothesis 5: Universities will be more likely to develop individual patents that are both highly cited and widely cited.

Hypothesis 6: Governments will be more likely to develop individual patents that are both highly cited and widely cited.

3. Data, measurement, and modeling strategy

3.1 Data

This article aims to determine whether the innovations developed by different types of organizations—firms, universities, and government research agencies—vary in regard to their importance and generality. Toward this end, we compile a novel dataset of patents assigned to highly-innovative representatives from each organization type over the period of 2006–10. Table 1 provides the summary statistics and source for each of the variables used in the analyses to follow.

The dataset draws from two complementary data sources: the Derwent Innovation Index (DII) and the EPO Worldwide Patent Statistical Database (PATSTAT). The DII was used to source all of the data regarding individual patent characteristics. PATSTAT was queried to attain information on the characteristics of each patent's forward citations.

To create our dataset, we begin with a list of highly-innovative assignees for each organization type.[8] All of the patents assigned to these organizations from 2006 to 2010 were collected and assigned to a bin based on whether the assignee was a firm, university, or government research agency. From each bin, we draw a random sample of 5,000 patents. After removing patents with missing information, those not listed in PATSTAT, and duplicate entries, we are left with a final dataset comprised 14,731 patents. Of these patents, 4,990 (33.87 per cent of the total) are corporate, 4,815 (32.69 per cent) are university, and 4,926 (33.44 per cent) are government.

3.2 Dependent variables

3.2.1 Importance

The first dependent variable considered here is technological importance. We operationalize technological importance using patent citation data. During the patent application process, patent applicants and the patent examiner are required to cite previous patents that reveal the state of the art for the innovation under consideration. The patents included in this prior art section represent the focal patent's antecedent technologies or the technologies, and their embedded knowledge, on which the underlying innovation relies. The number of times that a patent appears as prior art—its 'forward citations' count—is thus a direct measure of the extent to which a patent has been deemed important to subsequent innovation.

The practical import of forward citations is that it measures a patent's technological impact. Patents that are not cited by subsequent patents are 'a technological dead end' (Jaffe and de Rassenfosse 2017: 2). In contrast, highly-cited patents have been deemed by inventors, or patent examiners, as important to subsequent technological change.

For each patent in our dataset, we search 5 years of subsequent patenting in PATSTAT—from the focal patent's date of publication—for forward citations. The number of times a patent is cited within this 5-year window constitutes its measure of technological importance. Operationalization of importance using forward citations counts is validated by empirical evidence showing that forward citation correlates strongly with the opinions of knowledgeable peers about the technological significance of a given patent (Albert et al. 1991) and the patent's market value (Odasso et al. 2015). Similarly, Czarnitzki et al. (2011: 131) find that patents described by an employee of the World Intellectual Property Organization (WIPO) to have 'only marginally satisfy the "non-obviousness" criterion' receive fewer citations than those in a control group. Finally, the validity of the use of forward citations as a measure of the importance of a given patent is enhanced by considering a single very highly-cited patent. Azagra-Caro et al. (2017) identify Cohen and Boyer's process for creating molecular chimeras as the most highly-cited university patent over the period 1990–2007. This patent (US4237224) has been found to have had an enormous role in stimulating subsequent technological change (Feldman and Yoon 2012).

3.2.2 Generality

A perennial problem in the study of GPTs is what mht be termed the classification problem. That is, with the exception of a handful of clear-cut cases such as electricity and computers, it is often unclear which technologies should be included within the GPT category.[9] One way to circumvent this issue is to avoid discrete approaches to classification and assign a given innovation a nondiscrete measure of its 'generality'. Using this approach, a given patent is assigned a generality 'score' based on the extent to which its underlying intellectual property is broadly used by subsequent patents.

This is the approach taken here. In particular, we define generality as one minus the Herfindahl–Hirschman Index of the four-digit

Table 1. Descriptive statistics, full sample.

Variable	Obs.	Mean	Std. dev.	Min.	Max	Source
Dependent variable						
Forward citations	14,731	1.245	2.99	0	71	PATSTAT
Generality index	5,504	0.084	0.189	0	0.882	PATSTAT[a]
Generality 2 (unique IPC codes)	5,504	1.274	0.77	1	16	PATSTAT
Highly cited and highly general[b]	132 (0.89% of sample)					PATSTAT
Independent variables						
University assignee[b]	4,815 (32.7% of sample)					Derwent
Government assignee[b]	4,926 (33.4% of sample)					Derwent
Corporate assignee[b]	4,990 (33.9% of sample)					Derwent
Control variables						
No. of assignees	14,731	2.297	2.105	1	28	Derwent
Tech. breadth	14,731	2.621	1.538	1	16	Derwent
Jurisdictional coverage	14,731	3.052	3.586	1	62	Derwent

[a]Authors' calculations based on PATSTAT data.
[b]Category variable, 'Obs.', refers the representation of the category in question.

primary IPC codes for a given patent's forward citations. More formally:

$$G_i = \text{Generality}\mathit{Generality} = \ 1 - \sum_{j}^{n_i} S_{ij}^2.$$

such that S_{ij} is the ratio of the forward citations received by patent i that belongs to classification j. As the patents that cite a given patent come from an increasingly diverse set of IPC classifications, the generality index approaches one. In contrast, a patent that has accumulated all of its forward citations from a single IPC code will have generality index score of zero.

As an alternative measure of a patent's generality, we use the unique four-digit IPC codes from a given patent's forward citations. Each patent is assigned at least one IPC based on the technology field in which the patented invention falls. Patents that are cited by patents from a large number of technology classes are more general than those that are cited by patents from a small number of subfields. Thus, the count of the unique four-digit IPC codes that a patent draws its citations from is an alternative measure of the breadth of the patented technology.

3.2.3 Highly-cited and highly-general patents

In order to determine whether universities and governments are more likely to produce high-impact patents, we identify a subset of patents within our sample as being both highly cited and highly general. To define this subset of patents, we assign each patent in the sample to a quintile for both variables (forward citations and generality). Patents that are in the top quintile for *both* variables are assigned a value of 1.[10] Other patents are assigned a value of 0. Thus, the small subset of patents assigned a value of 1 (there were 132 in our sample) constitute patents that are amongst top 20 per cent of the distribution for citations received *and* generality. Of the 132 highly- and widely-cited patents in our sample, 29 (22 per cent) were produced by firms, 56 (42 per cent) were produced by universities, and 47 (36 per cent) were produced by government research agencies.

3.3 Independent variable

3.3.1 Organization type

The primary independent variable of interest is the organization type—firm, university, or government research agency—of a patent's assignee. In the analysis to follow, we set the reference group equal to patents assigned to firms. University patents are assigned a value of 1 and those assigned to government research agencies are assigned a value of 2.

3.4 Control variables

For a research design such as this, variables that have been consistently found to correlate with the study's dependent variables should be added as controls (King et al. 1994). We select a set of patent-level control variables based on this criterion. First, we control for the number of assignees on a patent. The technical or scientific complexity of an underlying invention is likely to correlate with the number of parties involved in the invention's development. Because a patent's importance and generality are also likely to correlate in relation to technical or scientific complexity, we add assignee counts to the models that follow.

To account for the technological breadth of the patented invention, we control for the number of Derwent Classification Codes that have been assigned to each patent. Patents assigned a large number of technology classes are likely to have greater technological coverage than those assigned a small number of subclasses (Harhoff et al. 2003). Because greater technological coverage is likely to be associated with differences in citation behavior, counts of technology classes are included in the regression models that follow.

Third, we add a control variable for the number of jurisdictions in which a patent has been filed. Sampat (2005) finds patents filed in multiple countries to be of higher quality than those filed in a single jurisdiction. Because patent quality is likely to correlate with both diffusibility and generality, a control for each patent's jurisdiction count is included. Finally, to control for inter-temporal variation, we include a set of patent application year dummy variables.

3.5 Models

To test the six hypotheses put forth in Section 2, three distinct dependent variables are used. These dependent variables require the use of three distinct modeling approaches. The dependent variable used to test Hypotheses 1 and 2 is 5-year forward citations. Forward citation data are counts (i.e. they are nonnegative and discrete) and, thus, suggest the use of the Poisson family of models (Hoffmann 2003). Because in our sample these data are overdispersed (the mean = 1.24 is higher than the variance = 2.99), a negative binomial regression model is estimated. The alpha parameters reported in

Table 2. Negative binomial regression of importance (forward citations), 2006–10.

	(1)	(2)
University assignee	0.285 (5.76)***	0.208 (4.15)***
Government assignee	0.093 (1.84)	0.014 (0.28)
No. of assignees		0.076 (8.16)***
Tech. breadth		0.032 (2.63)**
Jurisdictional coverage		0.028 (5.13)***
Year dummies	Yes	Yes
Constant	0.276 (4.45)	−0.039 (−0.55)
Wald χ^2	251.23***	380.83***
Alpha	3.60	3.50
Log pseudo-likelihood	−20,515	−20,435
Observations	14,731	14,731

All coefficients are unstandardized. Robust *z* statistics parentheses, standard errors are clustered at the basic country level; *P < 0.05, **P < 0.01, ***P < 0.001.

Table 3. Fractional probit regression of generality index, 2006–10, full sample.

	(1)	(2)
University assignee	0.334 (7.88)***	0.311 (7.21)***
Government assignee	0.291 (6.69)***	0.252 (5.70)***
No. of assignees		0.029 (4.23)***
Tech. breadth		0.017 (1.70)
Jurisdictional coverage		−0.000 (−0.23)
Year dummies	Yes	Yes
Constant	−1.613 (−29.54)***	−1.723 (−27.50)***
Log pseudo-likelihood	−1,548	−1,543
LR χ^2 (6, 9)	217.68***	238.73***
Observations	5,504	5,504

All coefficients are unstandardized. Robust *z* statistics parentheses, standard errors are clustered at the basic country level; *P < 0.05, **P < 0.01, ***P < 0.001.

Table 2confirm negative binomial regression to be preferable to Poisson models here. Consistent with the literature, the vast majority (62.84 per cent) of patents in our sample receive zero citations. To verify that 'excess zeros' do not drive the results, we also fit a zero-inflated negative binomial (ZINB) regression model.[11] In consideration of space, the results of the ZINB are presented in the Appendix. The curious reader will find that the results mirror those presented in Table 2.

The dependent variable used to test Hypotheses 3 and 4 is a patent's generality index score. The generality index assumes continuous values between 0 and 1. This characteristic makes linear regression inappropriate. While values of zero (i.e. when all of a patent's forward citations come from a single IPC class) are common in our data, the upper bound is never reached in the generality index. Because zero values are possible, beta regression is inappropriate. Under these conditions, Papke and Wooldridge (1996) recommend the use of fractional regression. We thus fit the generality index using a fractional probit regression with robust standard errors to correct for heteroskedasticity. Because calculating the generality index requires a patent to have been cited by subsequent patents, this model is estimated using the subset of 5,504 patents that received at least one forward citation within 5 years of their date of publication.

We test the robustness of the effect of organization type on generality (i.e. Hypotheses 3 and 4) in two ways. First, we estimate the fractional regression on a sub-sample of patents that received more than one forward citation. Because a fairly large proportion (14.78 per cent) of the patents that receive at least one citation receives only a single citation and a patent with a single citation will, by construction, have a zero generality index score, fitting the model to this alternative sample seeks to ensure that the observed relationship is not driven by these zero values. Second, we run the model using an alternative measure of generality: the number of unique IPC codes from a patent's forward citations. Unique IPC codes are counts, yet are not overdispersed, so a Poisson model is fit. Again, the regression tables for the robustness checks are provided in the Appendix. The results strongly mirror those presented in Table 3, suggesting our results to be robust to sample utilized and measure of generality.

Finally, the dependent variable used to test Hypotheses 5 and 6 is a binary variable. Patents that are both highly and widely cited are assigned a value of 1; other patents are assigned a value of 0. Thus, we use a probit model to test Hypotheses 5 and 6. In all of the models presented in Section 4 and the Appendix, Huber–White robust standard errors are used to correct for heteroskedasticity.

4. Results

Table 2 presents the results of our tests for importance. The analysis suggests that patents assigned to universities are cited more than those assigned to firms. This relationship is robust to the inclusion of controls (see model 2) and to the alternative (ZINB) specification (see Table A1 in the Appendix). This result supports that of Trajtenberg et al. (1997) who use a different patent data source and time period to find that university patents receive more citations that corporate ones.

Whereas the postulate that university patents will be more highly cited than corporate patents (Hypothesis 1) is supported by the data, we fail to find a similar effect for patents assigned to government research agencies. That is, we find no statistically significant difference in the number of citations accumulated by patents with government assignees.

Table 3 provides the results for the tests of Hypotheses 3 and 4. The analyses indicate that university and government patents are more general than those assigned to firms. Comparing the coefficients for University Assignee (0.311) and Government Assignee (0.252) to the standard deviation for the generality index (0.189) suggests that the organization effect size is large in magnitude. Tables A2 and A3 provided in the Appendix indicate that this relationship holds in the restrictive sample condition and using an alternative proxy for generality. In sum, Hypotheses 3 and 4 are strongly supported by the evidence provided here; university and government patents are significantly more general than their corporate counterparts.

Finally, Table 4indicates that universities and governments are more likely to produce individual patents that are both highly cited and highly general. That is, we find evidence in support of Hypotheses 5 and 6. Universities are particularly adept at developing such patents; 42 per cent of all of the patents that were in the top quintile for citations received and generality were assigned to universities.

Table 5summarizes the six hypotheses tests here. In general, our study supports the theoretical scholarship predicting that universities and government research agencies have a comparative advantage vis-à-vis firms in developing technologies with deep and wide impact.

Table 4. Probit regression of highly- and widely-cited dummy, 2006–10.

	(1)	(2)
University assignee	0.354 (4.28)***	0.334 (4.00)***
Government assignee	0.296 (3.62)***	0.267 (3.26)***
No. of assignees		0.047 (4.02)***
Tech. breadth		−0.001 (−0.08)
Jurisdictional coverage		0.010 (1.53)
Year dummies	Yes	Yes
Constant	−3.128 (−17.64)	−3.293 (−16.87)***
Log pseudo-likelihood	−721	−712
LR χ^2 (6, 9)	82.04***	101.85***
Observations	14,731	14,731

All coefficients are unstandardized. Robust *z* statistics parentheses, standard errors are clustered at the basic country level; *P < 0.05, **P < 0.01, ***P < 0.001.

Table 5. Results summary, hypothesis tests.

	Supported?
Hypothesis 1: importance, university > corporate	Yes
Hypothesis 2: generality, university > corporate	No
Hypothesis 3: importance, government > corporate	Yes
Hypothesis 4: generality, government > corporate	Yes
Hypothesis 5: high impact, university > corporate	Yes
Hypothesis 6: high impact, government > corporate	Yes

5. Conclusion

Do technological innovations developed by different types of organization vary with regards to their effect on subsequent technological progress? Here we have shown that they do and that organization effects in the United States are statistically robust and large in magnitude. Specifically, university patents are more general than corporate ones. Government patents are more highly cited and more general than corporate patents. Both university and government patents are more likely to belong to a small subset of patents that are both highly cited and highly general. While a detailed description of the policy implications of these results is beyond the scope of this article, it is worth briefly identifying the policy decisions with which these results may interact.

While there is large between and within group variation, each of the organization types examined here receives considerable public resources. In almost all countries, universities are tax exempt and receive large government grants. These outlays seek not only to increase access to higher education, but also to advance scientific research and promote economic development through the promotion of technological innovation (Schmid et al. 2017; Youtie and Shapira 2008). Our results provide circumstantial evidence that such public outlays to universities may be warranted. That is, our finding that university patents have a particularly deep and wide impact on subsequent technological change suggests that policies that attempt to use universities as engines for advancing technological innovation may hold promise.

However, our results should not be interpreted to suggest that contemporary university patenting approaches are socially optimal or that university patenting may not sometimes stifle subsequent innovation. Recent research (Eisenberg and Cook-Deegan 2018; Lemley 2008) contends that universities' pursuit of licensing revenue is often at odds with maximizing the pro-social impact of a given university-developed invention. Our results point toward the significant subsequent *technological* impact of university patenting and are agnostic regarding aggregate social impact or the effect of licensing policy.

Our findings also support the policy recommendations made by scholars such as Ruttan to publicly fund basic research via government research labs. Ruttan (2001, 2006a,b) asserts that governments are disproportionally responsible for the development of general technologies. This claim is based on his contention that governments—due to their lack of profit motive and long-time horizons—have a comparative advantage in the development of technologies whose returns are difficult to appropriate and whose viability requires the use of a low time-discount factor. The finding that governments in fact produce technologies that are more general than those produced by firms supports Ruttan's reasoning and his recommendation to publicly fund basic research.

This study, by considering a randomly-drawn sample, was designed to be agnostic regarding the technological field in which patenting occurs. This research design was selected so as to most effectively test the general theoretical claims described in Section 2. However, there is research merit in conducting a similar investigation for particular technological fields.[12] For example, considering whether there is organization-specific variation in patent characteristics within the field of pharmaceuticals could shed light onto whether the important role of universities in developing general purpose innovations, such as Cohen and Boyer's procedure for producing molecular chimeras or CRISPR-Cas9 gene-editing techniques, is a general phenomenon.

Finally, it is important to recognize that our research design does not allow us to make judgments about the counterfactual. It is possible that in the absence of public funding, firms would have developed a higher proportion of general patents. That is, further study is necessary to determine whether universities or government research labs crowd out certain types of private innovation. Nevertheless, our findings support the notion that universities governments have a comparative advantage in the development of high-impact technologies and that increased funding of such agencies may drive future technological innovation.

Notes

1. As of 26 July 2018, according to Google patents, patent US4237224 had received 313 citations. The mean number of forward citations in our sample is 1.24. The breath of US4237224's citations is chronicled in Feldman and Yoon's (2011) article.
2. In keeping with the terminological approach most commonly taken in the literature (Bacchiocchi and Montobbio 2009: 170l; Moser and Nicholas 2004: 389; Trajtenberg 2001: 364), the term 'importance' is defined very narrowly to refer to the degree to which a given patent has been critical to subsequent (patented) technological change. Other scholars (Lanjouw and Schankerman 2004; Sampat et al. 2003) have chosen to characterize a patent's accumulated citations as a metric of 'quality'. While this a perfectly reasonable characterization, we prefer to use the term 'importance' because it connotes the impact of the patent on *subsequent* technological change rather than describing an intrinsic feature of the patent of concern.

3. Patent applicants are required to list all patented technologies deemed relevant to the invention underlying the application within the 'prior art' section of their application documents. For a given patent, forward citations refer to the citations that a patent has received from future patents. Patents that receive a high number of forward citations can thus be said to have been important to the development of a large number of innovations.
4. The Electronic Frontier Foundation's 'Stupid Patent of the Month' <https://www.eff.org/issues/stupid-patent-month> column offers incisive and amusing commentary on this trend.
5. Rather than waves, Bresnahan and Trajtenberg (1995) describe the relationship between GPTs and their successor technologies using the analogy of a family tree. Within such a treelike diagram, GPTs are located at the top of the structure, their spawned technologies radiating downward and outward. The essential feature in both analogies is the role of GPTs in *initiating* future technological change.
6. The net effect of the difficulties associated with appropriating the returns to basic research is to decrease investment in basic research by decreasing the expected revenue associated with such projects. Nelson's framework assumes that, 'A rationally planned inventive effort will be undertaken only if the expected revenue of the invention exceeds the economic exceeds the expected cost' (Nelson 1959, p. 300). Holding other factors constant, a decrease in expected revenue results in this profitability criterion holding for fewer projects.
7. While on first blush, it may appear that if Hypotheses 1–4 are supported by the evidence, then Hypotheses 5 and 6 will follow as a matter of deduction. If this were the case, including Hypotheses 5 and 6 would be redundant. However, because Hypotheses 1–4 make *probabilistic* claims regarding the innovative output of different organization types, it is not possible to apply the logic of transitivity. For example, Hypotheses 5 and 6 make claims regarding a very small subset of innovations. In the empirical context considered here only 0.8% (132 of the 14,860 patents) of the sample are classified as highly and widely cited. It is thus possible that on average a given organization type will have patents that are more important and general than those of another organization type, while not developing a significantly higher number of the small subset of highly- and widely-cited patents.
8. The data appendix contains a comprehensive list of the assignees and a detailed description of the sampling strategy employed here. The author cleaned the data using Vantage Point (www.thevantagepoint.com), a text mining software.
9. Some scholars have even questioned the status of these apparently clear-cut GPTs. While Jovanovic and Rousseau (2005, p. 1182) cite electricity as one of the two 'most important GPTs so far', Moser and Nicholas (2004) fail to find evidence that electricity patents were more general than a control group. The failure of scholars to agree on what constitutes a GPT suggests that continuous metrics of generality (such as those used here) may be preferable to a binary classification.
10. Because in this portion of the analysis, we are interested in very high performing patents, we limit the quintile calculations to patents that receive at least one forward citation. If we had included the value of 0 in the quintile calculations, the cutoff point would have been two forward citations due to the high number of patents that are never cited. Our top quintile cutoff point is five forward citations. The top quintile cutoff point for generality is 0.586.
11. 'Excess zeros' refer to the zeros that exceed the distributional assumptions of the count distribution (in this case a negative binomial distribution).
12. The authors would like to thank an anonymous reviewer for providing this insight.
13. The IEEE Spectrum annual Patent Power reports do not have a single category for firms. Instead, the corporate entries are listed by sector (e.g. Chemicals, Computer Software, Electronics, etc.). Thus, in order to select the most innovative firms, we use the annual list of the top US patent holders that is issued by the Intellectual Property Owners Association. The annual releases of these data were collected from <https://www.ipo.org/index.php/publications/top-300-patent-owners/> (accessed 5 January 2017).

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Appendix

1. Sampling strategy

The dataset utilized in the proceeding analyses constitutes a concatenation of three purpose-built patent datasets: one comprised government-assigned patents, one comprised university-assigned patents, and one comprised firm-assigned patents. The source data used to create these datasets come from two complementary sources: the DII and the PATSTAT. The DII was used to source all of the data regarding individual patent characteristics. For each patent, PATSTAT was queried to attain information on the characteristics of each patent's forward citations.

For each organization type, we gather a random sample of 5,000 patents that were assigned to the most innovative US organizations within that organization type. In order to determine the most innovative organizations within each organization type, the following criteria were used.

1.1 Government patents

The twelve government research agencies included in the analysis constitute all of the US agencies listed in the government agencies sections of the annual IEEE Spectrum Patent Power lists from 2010 to 2015. Over the period of analysis used in the preceding analyses, these agencies were listed as assignees on 5,593 patents. From these 5,593 patents, a random sample of 5,000 was drawn to constitute the government patents sub-sample of the final sample.

The government assignees used in our analysis are: US Air Force, National Aeronautics and Space Administration, US Department of Energy, US Department of Agriculture, US Department of Commerce, US Department of Veterans Affairs, National Security Agency/Central Security Service, US Navy, US Postal Service, US Army, US Department of Health and Human Services, and the US Environmental Protection Agency.

1.2 University patents

The forty universities included in the analysis constitute all of the US universities listed in the university section of the annual IEEE Spectrum Patent Power lists from 2010 to 2015. Over the 2006–10 period of analysis, these universities were listed as assignees on 22,047 patents. A random sample of 5,000 patents was drawn to constitute the university patents sub-sample of the final sample.

The university assignees used in our analysis are: California Institute of Technology, University of Colorado, Cornell University, Georgia Institute of Technology, Harvard University, Indiana University, Iowa State University of Science and Technology, Massachusetts Institute of Technology, Northwestern University, The Ohio State University, University of California, Rice University, Rensselaer, Stanford University, University of Texas, Tufts University, University of Massachusetts, University of Maryland, University of Illinois, University of Iowa, University of Washington, University of Michigan, University of Pennsylvania, University of Southern California, University of Utah, Clemson University, Carnegie Mellon University, Columbia University, University of Central Florida, Loma Linda University, University of Miami, North Carolina State University, New York University, State University of New York (SUNY), Oregon State University, Purdue University, University of South Carolina, University of South Florida, University of Wisconsin, and Virginia Polytechnic Institute.

1.3 Corporate patents

The sixteen firms included in the analysis constitute all of the US firms that fell within the top ten patent owners from 2010 to 2015. The Intellectual Property Owners Association compiles the list of top patent owners.13 Firms that have been acquired (Broadcom

Corporation) are included in the analysis, as their patents still receive citations from subsequent patents. These sixteen organizations are listed as assignees on over 100,000 patents during the period of analysis. A random sample of 5,000 of these patents was used here to constitute the corporate patents sub-sample of the final sample.

The firm assignees used in our analysis are: IBM, Microsoft, Intel, Hewlett-Packard, General Electric, Oracle, Cisco Systems, Honeywell, Xerox, AT&T, Broadcom, General Motors, Qualcomm, Google, Apple, and Ford.

1.4 The final sample

The final dataset utilized in the proceeding statistical analyses constitutes the concatenation of the three 5,000 patent samples. After removing patents with missing information, those absent from PATSTAT, and duplicates, we were left with a final dataset comprised 14,731 patents. Of these four samples, 990 (33.87 per cent of the total) are corporate patents, 4,815 (32.69 per cent) are university patents, and 4,926 (33.44 per cent) are government patents.

2. Robustness checks

Table A.1. ZINB regression of importance (forward citations), 2006–10.

	Logistic (1)	Negative binomial (1)
University assignee		0.304 (6.06)***
Government assignee		0.222 (4.21)***
No. of assignees	−0.796 (−2.52)*	0.025 (2.68)**
Tech. breadth	−0.01 (−0.23)	0.016 (1.31)
Jurisdictional coverage	−3.00 (−5.20)***	0.004 (0.86)
Year dummies	Yes	Yes
Constant	3.686 (4.32)***	0.251 (3.38)**
Wald χ^2 (9)	187.47***	
Log pseudo-likelihood		−20,105
LN α		0.996***
Observations	14,731	14,731

All coefficients are unstandardized. Robust z statistics parentheses; *P < 0.05, **P < 0.01, ***P < 0.001.

Table A.2. Fractional probit regression of generality index, 2006–10, restricted sample (two or more forward citations).

	(1)	(2)
University assignee	0.338 (7.26)***	0.316 (6.66)***
Government assignee	0.329 (6.94)***	0.293 (6.07)***
No. of assignees		0.025 (3.22)**
Tech. breadth		0.174 (1.58)
Jurisdictional coverage		−0.001 (−0.29)
Year dummies	Yes	Yes
Constant	−1.363 (−22.95)***	−1.459 (−21.57)***
Log pseudo-likelihood	−1,307	−1,304
LR χ^2 (6, 9)	182.35***	196.14***
Observations	3,316	3,316

All coefficients are unstandardized. Robust z statistics parentheses, standard errors are clustered at the basic country level; **P < 0.01, ***P < 0.001.

Table A.3. Poisson regression of unique IPCs of forward citations, 2006–10.

	(1)	(2)
University assignee	0.137 (6.72)***	0.130 (6.32)***
Government assignee	0.113 (5.41)***	0.098 (4.68)***
No. of assignees		0.013 (4.05)***
Tech. breadth		0.002 (0.36)
Jurisdictional coverage		−0.001 (−0.33)
Year dummies	Yes	Yes
Constant	0.99 (4.31)***	0.641 (2.37)*
Wald χ^2 (6, 9)	182.38***	195.48***
Log pseudo-likelihood	−6,664	−6,661
Observations	5,504	5,504

All coefficients are unstandardized. Robust z statistics parentheses, standard errors are clustered at the basic country level; *P < 0.05, **P < 0.01, ***P < 0.001.