On the transfer of technology from universities: The impact of the Bayh–Dole Act of 1980 on the institutionalization of university research

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Abstract:

While the academic and policy literature has focused on patent counts and patent quality as possible outcome measures to evaluate the impact of the U.S. Bayh–Dole Act of 1980, we argue that the impact of the Act on university effort to transfer its technology to the private sector might be seen more accurately by examining the trend in the initial establishment of technology transfer offices (TTOs). Using an econometric framework to identify the presence of multiple structural breaks in data on the annual number of university TTOs, we find multiple break dates over the period 1925 to 2014. One break date was in the late-1960s and a second break date occurred about 1982. We suggest, in contrast to previous findings in the literature, that the Act did have an impact on the formal internal transfer of technology from universities through patenting by providing an incentive for universities to invest in a TTO research infrastructure. We also suggest that our empirical methodology is applicable to an assessment of the impact of legislation similar to the Bayh–Dole Act in the many countries with such legislation.

Keywords: Bayh–Dole Act | Technology transfer | Patenting | Structural change

Article:

1. Introduction

On February 9, 1979, Senator Birch Bayh introduced Senate bill S. 414 before the 96th U.S. Congress, The University and Small Business Patent Procedures Act. The objective of this Act is "to promote utilization of inventions arising from federally supported research or development." After a series of debates about this proposed legislation, on December 12, 1980, President Jimmy Carter signed, Public Law 96-517, Amendments to the Patent and Trademark Act (part of which was originally known as the University and Small Business Patent Procedure Act of 1980). It is this amendment that is commonly referred to as the Bayh–Dole Act of 1980.[1] The Act allowed universities to patent and license federally funded inventions developed by their faculty and staff provided that the faculty/staff member disclose to the university his/her inventions, and that the university disclose to the funding agency its intention to take ownership of the invention.

The literature, to date, has evaluated the impact of the Bayh–Dole Act by comparing patenting activity at universities in the periods before and after the Act was implemented. This approach has mostly yielded mixed evidence, as recently reviewed by Grimaldi, Kenney, Siegel, and Wright (2011), and others. While scholars generally agree that university patenting activity did increase in the post-1980 periods, many are unable to identify precisely if the upward trend began prior to or in response to the Bayh–Dole Act. Those contending that the upward trend began prior to the Act point to changes in the research culture at universities (e.g., Berman, 2008, Berman, 2012) and to the biotechnology revolution (e.g., Kenney, 1986). Previously, none of the scholars to date have considered the presence of requisite infrastructure across universities, namely technology transfer offices (TTOs), needed to transfer university-based technologies.[2]

In this paper, we present new evidence about the impact of the Bayh–Dole Act on university behavior. Shortly after the Act, and perhaps in response to the Act, many universities began to establish infrastructures to receive faculty/staff invention disclosures and to handle the subsequent patenting and licensing process of their inventions (Bradley, Hayter, and Link, 2013). The genesis of such a formal internal patenting and licensing process for these universities was the establishment of a TTO.[3]

Fig. 1 shows both the annual number and the cumulative number of U.S. university TTOs, by year of establishment, as reported by the Association for University Technology Managers (AUTM).4 Regarding both the year-by-year figures and the cumulative figures, there appears from Fig. 1 to have been an increase in the number of newly established TTOs beginning in the early to mid-1970s followed by a greater increase shortly after the passage of the Act in 1980. Around year 2000, the rate of TTO establishment appears to have slowed down as most research universities had already established such an office by then.

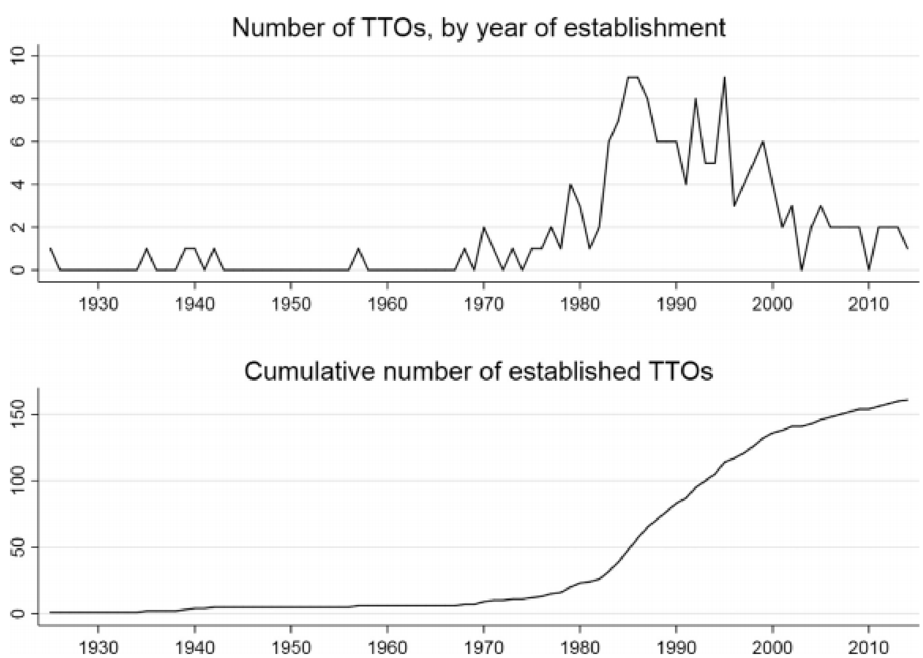

Fig. 1. U.S. University TTOs, by year of establishment (1925–2014).

The purpose of this paper is to explore empirically the relationship between the passage of the Bayh–Dole Act and the actions by universities to establish TTO infrastructures to support formal university technology transfer through patenting and licensing. In particular: Was the passage of the Act associated with an increase in university TTOs that were previously nearly nonexistent, or did the Act accelerate a pattern of university TTO formation, and thus of patenting activity, that had already begun? If we conclude from our analyses that the empirical evidence supports a significant increase in the number of TTOs shortly after the passage of the Act, then our evidence suggests that the Act did meet an aspect of its purpose, namely initiating appropriate university infrastructure "to promote utilization of [university] inventions arising from Federally supported research or development."

In Section 2, we briefly review aspects of the relevant literature related to the impact of the Bayh–Dole Act on U.S. university technology transfer activity. Our review shows that prior research has focused on university patenting activity as the relevant technology transfer metric through which to assess the impact of the Act; however, our argument is that formal university patenting generally begins after the establishment of a TTO.[5,6] In other words, patenting patterns alone do not tell us about institutionalization, and we argue that institutionalization should be considered as an important metric when evaluating the impact of the Bayh–Dole Act.

The impact of the Act on creating an infrastructure to engender or leverage university technology transfer activity through patenting and licensing has not previously been considered. A dominant conclusion from the literature, which is based on the assumption that the effectiveness of the Act can be revealed empirically through a single structural change in university patenting activity over time (i.e., an observed change in patenting activity before versus after the passage of the Act), is that the increase in university patenting began prior to the passage of the Act in 1980. This finding has been interpreted in the literature to mean that the Act itself did not have a significant impact on university patenting behavior.

In Section 3, we propose a statistical test for assessing the institutionalization impact of the Bayh–Dole Act. Using only data on the number of TTOs established each year, standard micro-econometric approaches for policy evaluation, such as differences-in-differences or regression discontinuity designs, are not feasible. Instead, we investigate whether a break in the series occurred around the time the Bayh–Dole Act was passed. Fixing the time of the break in 1980, however, is not desirable, since anticipatory or delayed effects of the Act could have occurred before or after 1980. We therefore use an empirical test for the presence of one or more structural breaks with unknown break dates. We present our statistical findings in Section 4, and we conclude in Section 5 that our empirical evidence does suggests that the Act did in fact provide a strong (i.e., statistically significant) institutional incentive for universities to invest in research infrastructure and thus to position themselves to transfer formally and internally faculty/staff inventions through patents.[7] We also suggest that our empirical methodology is applicable to an assessment of the impact of legislation similar to the Bayh–Dole Act in the many countries with such legislation.

2. An overview of the literature related to the impact of the Bayh-Dole Act

The literature related to an assessment of the impact of the Bayh–Dole Act has focused on both university patent counts and the quality of university patents as possible metrics to evaluate the impact of the Bayh–Dole Act.8 Our paper suggests that evidence of an impact of the

Act on university effort to transfer its technology might be seen more directly by examining the trend in the establishment of university TTOs.

TTO infrastructures are generally prerequisite to formal internal university patenting and formal faculty engagement in technology transfer activity. However, a widely-cited segment of the patenting literature related to the Bayh–Dole Act has been primarily, but not exclusively, case based using information from selected universities that had established a TTO prior to 1980. For example, Mowery, Nelson, Sampat, and Ziedonis (2001) show that Stanford University and the universities in the California system established their TTOs prior to the Act, and that these two universities began to patent before 1980. Also included in their study was Columbia University. Columbia University's TTO opened in 1982, and it began to become involved in university patenting after that date. In another segment of the literature, Henderson, Jaffe, and Trajtenberg (1998) and Mowery, Sampat, and Ziedonis (2002), for example, showed empirically a statistical increase in aggregate university patent activity prior to the passage of the Act.

Berman (2008, p. 836) characterizes the conclusion that the increase in university patenting in the 1980s and beyond was a result of the Bayh–Dole Act as "problematic." She argues that university patenting is in itself an institution that develops over time, and it is unlikely that a single event (i.e., the Bayh–Dole Act) will cause a university to go from not patenting to patenting. But, as we argue here, generally a necessary condition for a university to go from not patenting to patenting is the institutional presence of a TTO.

Berman (2012, p. 14) makes the argument that universities in the aggregate began to experiment with "market-logic" activities as early as the late-1950s and 1960s, noting as examples the formation of university research parks, the establishment of industry affiliates programs, and university involvement in extension programs. Berman (2012, p. 42) also identifies several so-called experiments in the 1970s that were instrumental in allowing universities to capture the economic benefits of market logic, namely "faculty entrepreneurship in the biosciences, university patenting, and university-industry research centers." These actions and programs, and others, focused on "the economic value of science, as opposed to its knowledge value or some other noneconomic purpose … [yet] market logic nevertheless remained limited in scope" (Berman, 2012, p.29).

Relatedly, Mowery et al. (2001; 2002), and Mowery (2005) suggested that the upward trend in university patenting that began in the 1970s and accelerated in the 1980s might have occurred even in the absence of the Bayh–Dole Act. To this point, one might suggest that the post-1980 increase in patenting observed in the aggregate is simply a consequence to a pre-1980 increase in patenting by universities that already had established a TTO. The observed post-1980 increase in patenting by such universities reflects a trajectory established before the Act.

Mowery et al., 2001, Mowery et al., 2002), and Mowery (2005) also correctly point to the fact that many research universities, such as Stanford University, had shifted to biomedical research and biotechnology in the aftermath of Congress removing restrictions on patents related to recombinant DNA in the late-1970s. This increase in biomedical and biotechnology-related patenting was also leveraged by the Supreme Court's decision in Diamond vs. Chakrabarty in 1980.[9]

Kenney (1986), through his historical trace of the university-to-industry relationships in the biotechnology revolution years, discusses in detail not only university emphasis on biotechnology-related patenting but also the external infrastructures for patenting that some universities were using well before the Bayh–Dole legislation even began.[10] The Research Corporation, University Patents, and the Wisconsin Alumni Research Foundation are examples of such organizations. As Kenney explains (1986, p. 74): "[Such organizations] act as a buffer between the university and the corporation seeking to license a university invention. In many universities the cost of a patent office with its ancillary staff is not warranted because of the limited number of inventions. In these cases, entities such as Research Corporation and University Patents can be useful, and both have become involved in licensing genetically engineered organisms and other biotechnology patents."[11] That said, the Bayh–Dole Act might have incentivized such research universities to establish their own internal technology transfer infrastructure.[12]

3. Our statistical methodology

While the establishment of TTO infrastructures is generally prerequisite for formal internal university patenting and licensing, analyzing the impact of the Bayh–Dole Act in terms of actual patenting behavior is appealing because the enabling legislation focuses specifically on patents. But, if there are multiple stages of changes in the university's research environment, analyzing a time series about the establishment of requisite infrastructures to facilitate changes in patenting behavior offers not only an intuitive approach to understanding the implications of the Bayh–Dole Act, but also a statistical advantage in quantifying an impact of the Act. Thus, the empirical question that we ask in this paper becomes: Is there evidence to suggest that the establishment of TTOs increased after the passage of the Bayh–Dole Act? We investigate an answer to this question by analyzing data on the number of TTOs that were established at U.S. universities each year over the period 1925−2014.[13]

As is apparent from the upper display in Fig. 1, the pace at which new TTOs were being established noticeably increased in the early-1980s. From 1925 through 1979, an average of 0.4 TTOs were established each year. During the period 1980−2014, the annual number increased about 10-fold. A t-test comparing the means of TTO establishments before and after 1980 yields a t-statistic of 9.8 and a p-value near zero, providing strong evidence that the Bayh–Dole Act had an impact on the rate of TTO establishment.

The simple t-test is a special case of the Chow test for a structural break (Chow, 1960). Its application, of course, requires that the break occurs at a known point in time. As noted in the Introduction, however, choosing a fixed break date of 1980 is somewhat arbitrary and may be misleading if, for example, the Act had a delayed effect. If it is unclear if and when exactly a break occurred, as is the case for the TTO data in Fig. 1, the Chow test could be repeated for a number of different break dates. However, conducting multiple hypotheses tests in this way can lead to results that are not necessarily consistent (e.g., rejecting the null of parameter stability with a 1980 break date, but not rejecting it with, say, a 1984 break date) and increase the probability of a type I error. The exact timing of the break could also remain ambiguous.

A solution to this break date identification problem is to apply a test for structural change with an unknown break date. The idea behind this test, which dates to Quandt, 1958, Quandt, 1960), is to calculate the Chow or Wald test for a range of break dates and use the maximum value as the test statistic. The point in time at which the maximum occurs serves as an estimator of the break date.14 In our analysis, we also use two modified Wald statistics, proposed by Andrews (1993) and Andrews and Ploberger (1994), that have better power properties. Finally, because the Bayh–Dole Act is only a single event that may have impacted the establishment of TTOs, we cannot rule out additional structural breaks. We therefore follow Bai (1997b) and Hansen (2001) and use these tests iteratively, based on repeated splitting of our sample, to test for an unknown number of structural changes with unknown break dates. See the Appendix for more details about our econometric test method.

4. Our statistical findings

We first parallel the literature and present findings from testing for a single structural break in the data in the top display in Fig. 1. The values of the Wald statistic for break dates between 1938 and 2000 are plotted in Fig. 2.15 The maximum value of 74.17 occurred for a break date of , suggesting that the rate at which new TTOs were established at universities, and consequently the moment when university patenting began to increase, might have occurred several years prior to the passage of the Bayh–Dole Act. This finding supports the general, but undated by year, conclusions of Mowery et al. (2001) and Berman, 2008, Berman, 2012), and others as discussed above.[16] As shown in Table 1, all three versions of the Wald test overwhelmingly reject the null hypothesis that no break was present, with p-values close to zero.

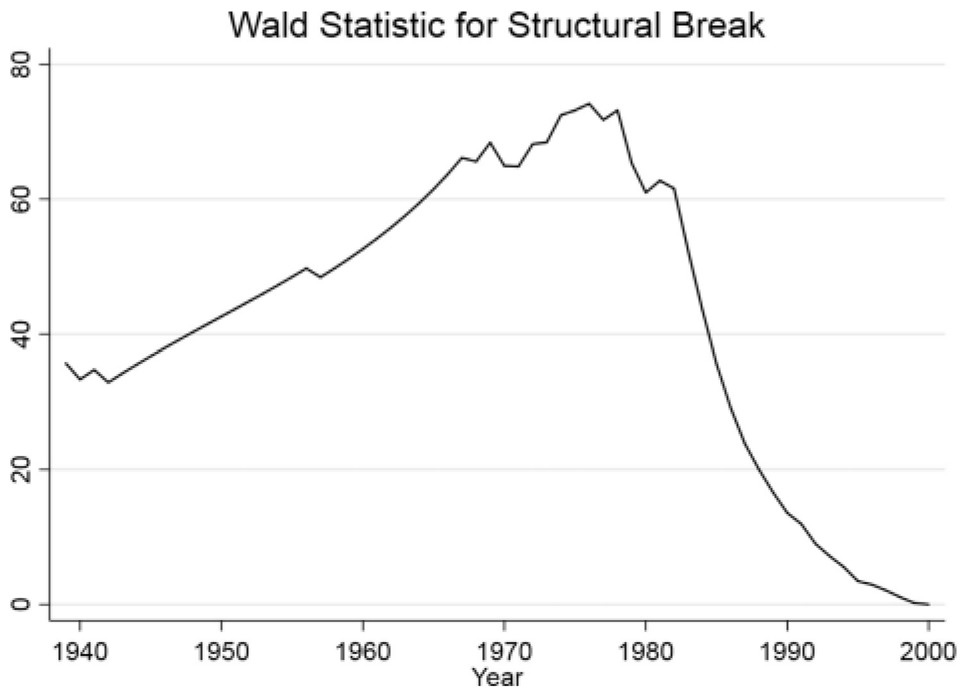

Fig. 2. Wald statistic, by year of structural break.
Note: The maximum value of the Wald statistic (74.17) occurred in 1976. The 95% confidence interval for the break date is [1970,1977].

Table 1
Tests for a single structural break: statistics, critical values and *p*-values

Test statistic	Value	5% Critical value†	p-value††
Max-W	74.17	8.85	<0.0001
Ave-W	42.58	2.88	<0.0001
Exp-W	34.12	2.06	<0.0001

† Critical values taken from Andrews (1993) and Andrews and Ploberger (1994).
†† p-values calculated by the approximation of Hansen (1997).

Table 2
Test results for multiple structural breaks

Iteration	Subsample	Max-W	Ave-W	Exp-W	Break date	Confidence interval (95%)
1	1925–2014	74.17 (<0.001)	42.58 (<0.001)	34.12 (<0.001)	$\hat{T}_0 = 1976$	1970–1977
2	1925–1976	7.80 (0.072)	1.89 (0.126)	1.62 (0.085)	$\hat{T}_1 = 1967$	1954–1970
	1977–2014	36.63 (<0.001)	16.00 (<0.001)	15.78 (<0.001)	$\hat{T}_2 = 2000$	1999–2007
3	1925–2000 (re-test $\hat{T}_0$)	154.95 (<0.001)	57.18 (<0.001)	73.53 (<0.001)	$\hat{T}_3 = 1982$	1980–1983
	1983–2014 (re-test $\hat{T}_2$)	74.17 (<0.001)	41.45 (<0.001)	34.03 (<0.001)	$\hat{T}_4 = 2000$	1999–2003
4	1925–1982	16.95 (<0.001)	7.93 (<0.001)	6.06 (<0.001)	$\hat{T}_5 = 1969$	1960–1970
	1983–2000	11.69 (0.012)	5.74 (0.004)	3.98 (0.004)	$\hat{T}_6 = 1995$	1992–2000†
	2001–2014	1.48 (0.913)	0.55 (0.605)	0.31 (0.631)	$\hat{T}_7 = 2009$	2001–2014†
5	1970–1995 (re-test $\hat{T}_3$)	88.71 (<0.001)	33.95 (<0.001)	41.47 (<0.001)	$\hat{T}_8 = 1982$	1980–1983
	1996–2014 (re-test $\hat{T}_4$)	21.57 (<0.001)	8.69 (<0.001)	8.28 (<0.001)	$\hat{T}_9 = 2000$	1998–2003
6	1925–1969	2.87 (0.581)	0.71 (0.492)	0.45 (0.483)	$\hat{T}_{10} = 1942$	1926–1969†
	1970–1982	5.80 (0.175)	2.87 (0.050)	1.87 (0.062)	$\hat{T}_{11} = 1976$	1970–1979†
	1983–1995	4.14 (0.354)	1.29 (0.242)	0.91 (0.225)	$\hat{T}_{12} = 1987$	1983–1994†

Note: for the Max-W, Ave-W and Exp-W statistics, p-values are given in parentheses.
† Trimmed confidence interval. The untrimmed interval extends beyond the bounds of the estimation sample.

The average rates of TTO establishment before and after the break are $\bar{y}_0(\hat{T}_0) = 25$ and $\bar{y}_1(\hat{T}_0) = 3.89$, while the estimated variance changes from $\hat{\sigma}_0^2(\hat{T}_0) = 0.23$ before the break to $\hat{\sigma}_1^2(\hat{T}_0) = 6.64$ after the break. Given this large difference in variance, the asymptotic distribution of the (standardized) break date estimator is highly asymmetric, with 2.5th and 97.5th percentiles of and 343.86, respectively. The resulting 95% confidence interval for the break date is [1970, 1977]. The evidence thus indicates that a shift in the rate of TTO establishment likely occurred sometime in the early to mid-1970s. The confidence interval has a wide range that is highly asymmetric around 1976. This, again, occurs due to the large change in variance. While Fig. 1 suggests that a break occurred closer to 1980, the confidence interval shows that we cannot rule out a break in the early 1970s: the annual number of TTOs established only ranged between 0 and 2 during those years, but a break may in fact have occurred early, and the low counts could have arisen because of the high variability in the outcome after the break.

However, the estimated single break date of 1976 may be misleading if more than one break had occurred. In fact, an inspection of Fig. 1 suggests that the rate of new TTO establishment may have first increased around 1970, increased again and more substantially around 1980, and finally decreased sometime around 2000. We therefore apply the iterative procedure discussed in Hansen (2001) and described in more detail in the Appendix. The results are given in Table 2.

As discussed above, in the full sample we reject the null hypothesis of no structural break and find a break in 1976 (see the row labeled 'Iteration 1'). We subsequently split the sample at

1976 and test for a single structural break in each subsample (Iteration 2). The three Wald tests show that there is weak evidence of a break in the period [1925, 1976]. A break is estimated at $\hat{T}_1 = 1967$, but the associated confidence interval [1954, 1970] is very wide. In the period [1977, 2014] all three Wald statistics are highly significant. The estimated break date in this subsample is $\hat{T}_2 = 2000$, which is also estimated rather imprecisely.

In Iteration 3, we proceed to re-test the significant break dates (1976 and 2000). In the period [1925, 2000] the Wald statistics and associated p-values again provide strong evidence of a structural break, but this is now estimated to occur at $\hat{T}_3 = 1982$. Inspection of Fig. 1 also suggests that within this subsample 1982 is a more likely break date than 1976. Moreover, the break date is estimated more precisely, with a 95% confidence interval of [1980, 1983]. Tests in the interval [1983, 2014] are highly significant and, again, point to a structural break in 2000.

In Iteration 4, we split the sample according to the significant break dates identified so far (1982 and 2000) and test for a structural break within each subsample. All tests strongly reject the null hypothesis of no break in the subsamples [1925, 1982] and [1983, 2000], with estimated break dates of 1969 and 1995. In Iteration 5, we re-test the earlier found break dates. The subsample [1970, 1995] confirms the existence of a structural break in 1982 (with 95% confidence interval [1980, 1983]), whereas the subsample [1996, 2014] confirms the existence of a break in 2000 (with 95% confidence interval [1998, 2003]).

Finally, in Iteration 6, we split the sample into subsamples based on the break dates 1969, 1982, 1995 and 2000.[17] The Wald statistics and corresponding p-values provide no evidence of further structural breaks. Inspection of Fig. 1 also suggests that no break occurred in the period [1925, 1969]. This is harder to determine graphically for the remaining periods. These periods are all relatively short and the power of the Wald tests is expected to be very low.

In summary, our analysis points to the presence of four structural breaks in 1969, 1982, 1995 and 2000, which split our sample in five periods. Table 3 shows summary statistics for each of these periods. After the first estimated break in 1969, the average rate of TTO establishment jumped from 0.16 per year to 1.46 per year. In 1982, two years after passage of the Bayh–Dole Act, there was another jump of a much larger magnitude. After 1995 the rate appears to have decreased in two stages: from 6.77 per year in the period 1983–1995 to 4.4 per year in the period 1996–2000, and finally down to 1.79 per year in 2001–2014.

Table 3
Subsample summary statistics for TTO establishment dates

Subsample	Mean	Standard deviation
1925–1969	0.16	0.37
1970–1982	1.46	1.13
1983–1995	6.77	1.69
1996–2000	4.4	1.14
2001–2014	1.79	0.89

The policy implication of our findings is that there was an increasing trend in the establishment of university TTOs well prior to the enactment of the Bayh–Dole Act, but that trend accelerated further shortly after the passage of the Act. Thus, our results suggest that while in the aggregate the Act did not in itself initiate the establishing of university TTOs, and thus did not initiate a university movement to patenting, it did have a measurable impact on enhancing that behavior for a period of time and then decreasing in impact.

5. Concluding remarks

In this paper we investigated the relationship between the passage of the Bayh–Dole Act and the establishment of TTO infrastructure at universities. Whereas the literature has focused on university patenting activity as the relevant metric for assessing the technology impact of the Act, we suggest that the establishment date of TTOs relative to the passage of the Act is also an appropriate metric, and in fact it might be a more appropriate one. Our argument is that formal university patenting generally begins after the establishment of a TTO.

We adopt the testing framework developed and outlined in a series of papers by Andrews, 1993, Andrews and Ploberger, 1994 and Bai, 1994, Bai, 1997a, Bai, 1997b), and we test for the presence of multiple structural breaks in data on the annual number of TTOs established at U.S. universities.

Our results show that multiple structural breaks occurred. In the late-1960s, well before passage of the Bayh–Dole Act, the rate of TTO establishment increased slightly. A second and more substantial break occurred around 1982, shortly after passage of the Bayh–Dole Act, when the rate of TTO establishments increased significantly (in a statistical sense). Thus, we interpret this finding as support for the argument that the Act provided an incentive for universities to establish a TTO and thus to position themselves for formally transferring faculty inventions through patent licensing. Finally, our analysis also shows evidence that the rate of TTO establishment started to decrease after 1995 and even more so after 2000. These patterns may signal a saturation effect: by the end of the 1990s, many research universities had already established a TTO.

Our analysis also illustrates a methodology that is applicable to an assessment of the impact of legislation similar to the Bayh–Dole Act in the many countries with such legislation.18 Interestingly, in China the 2002 ruling, "Measures for Intellectual Property Made under Government Funding," is often called "Chinese Bayh–Dole Act" (Fisch, Block, Philipp, and Sandner, 2016). Similarly, in Japan, the "Japanese Bayh–Dole Act" is part of the 1999 "Industrial Revitalizing Special Law" (Takenaka, 2005).

Finally, in addition to offering an alternative assessment view about the Bayh–Dole Act, our analysis suggests the need for additional research into aspects of the institutional nature of university TTOs and the patents they handle.19 In particular, little is known about how the shift, among some universities, from reliance on what we referred to as patenting agents to an institutional TTO changed patenting behavior. In particular: Did the newness or the quality of patents change after the establishment of the TTO? Future research might address this issue.

Perhaps it is the case that patents in those universities that relied on patenting agents are different in some dimensions from patents that originated at universities who first began to patent after their TTO was founded. Little is also known about the establishment of new university startup firms, also a relevant mode of university commercialization, in the pre- and post-Bayh–Dole periods. As scholarly research about the impact and influence of the Bayh–Dole Act continues, not only using data relevant to the United States but also to other nations, we might also learn more about the relative importance of formal technology transfer mechanisms such as patents, licenses, and new firm startups for the commercialization of university knowledge, as well as about informal technology transfer mechanisms such as publication (Balven, Fenters, Siegel, and Waldman, 2018).20 Another area for future research might compare and contrast technology transfer activities from universities with those from national or federal laboratories. Areas of comparison might include both motivations for the activities, mechanisms used, and the overall economic benefits from such activities (Fini et al., 2019, Link and Scott, 2019).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi: 10.1016/j.euroecorev.2019.08.006.

Appendix: Details of the Econometirc Test Method

In this Appendix, we provide additional details about the different test statistics reported in Tables 1 and 2.[21] We also discuss the estimator for the break dates and the (non-standard) distribution theory needed to construct confidence intervals. Specifically, let y_t be the number of TTOs established in year $t = 1, \ldots, T$, where $t = 1$ corresponds to 1925 and $t = T$ corresponds to 2014. The model generating y_t can be written as

$$y_t = \beta_0 + \beta_1 D_t(\tau_0) + \varepsilon_t,$$

A structural break occurs in year τ_0 if $\beta_1 \neq 0$. Since τ_0 and β_1 are both unknown, we proceed to test for both the presence and location of a structural break. For a pre-specified break date τ, we first calculate the Wald statistic $W(\tau)$ to test the null hypothesis that β_1 is zero:

$$W(\tau) = (\bar{y}_1(\tau) - \bar{y}_0(\tau))^2 \left(\frac{\hat{\sigma}_1^2(\tau)}{n_1(\tau)} + \frac{\hat{\sigma}_0^2(\tau)}{n_0(\tau)} \right)^{-1}.$$

Here, $\bar{y}_0(\tau)$ and $\bar{y}_1(\tau)$ are the sample averages of yt in the assumed pre-break ($t \leq \tau$) and post-break ($t > \tau$) periods, respectively, $n_0(\tau)$ and $n_1(\tau)$ are the corresponding sample sizes, and $\hat{\sigma}_0^2(\tau)$ and $\hat{\sigma}_1^2(\tau)$ are estimates of the variance of ε_t in the pre- and post-break periods.[23]

The Wald statistic can now be recalculated for a range of break dates. Following Andrews (1993), we consider all break dates in the interval $[\tau_L, \tau_U]$ such that the pre-break period contains between 15% and 85% of the total number of observations.[24] From the resulting set of Wald statistics, we calculate the maximum $Max - W = Max_{\tau_L \leq \tau \leq \tau_U} W(\tau)$ and the corresponding p-value.[25] For comparison purposes, we also calculate the average and exponential forms of the Wald test, which have better power properties (Andrews and Ploberger, 1994):

$$\text{Ave} - \text{W} = \frac{1}{\tau_U - \tau_L + 1} \sum_{\tau_0 = \tau_L}^{\tau_U} W(\tau)$$

$$\text{Exp} - \text{W} = ln\left(\frac{1}{\tau_U - \tau_L + 1} \sum_{\tau_0 = \tau_L}^{\tau_U} exp\left(\frac{1}{2} W(\tau)\right)\right)$$

The aforementioned tests help determine whether or not a structural break occurred. A natural estimator for the unknown break date is the value $\hat{T}_0$ for which the Wald statistic is maximal. This date, however, is only a point estimate of the break date. To construct a confidence interval that accounts for uncertainty in the break date, a sampling distribution for the break date estimator is needed.[26]

Since we are essentially using least squares to estimate a structural break in a linear model, we adapt Bai's (1997a) Proposition 3 for the limiting distribution of the break date estimator. In our context, his proposition specializes to

$$\frac{(\bar{y}_1(\tau_0)-\bar{y}_0(\tau_0))^2}{\sigma_0^2(\tau_0)}\left(\hat{\tau}_0-\tau_0\right)\xrightarrow{d}\arg\max_s Z(s),$$

where Z (s) is defined as

$$Z(s)=\begin{cases} W_1(s)-\frac{|s|}{2}, & \text{if } s\le 0\\ \sqrt{\frac{\sigma_1^2(\tau_0)}{\sigma_0^2(\tau_0)}}W_2(s)-\frac{|s|}{2}, & \text{if } s>0.\end{cases}$$

Here, $W_1(s)$ and $W_2(s)$ are two independent standard Wiener processes, starting at the origin when s = 0. The CDF of arg $\max_s Z(s)$ is derived in Bai (1997a, appendix B). The distribution is asymmetric, unless $\sigma_0^2(\tau_0) = \sigma_1^2(\tau_0)$. For $\alpha \in (0, 0.5)$, let $c_{\alpha/2}$ and $C_{1-\alpha/2}$ be the 100α/2 % and 100(1-$\alpha/2$)% quantiles of this distribution. Given consistent estimators $\hat{T}_0$, $\hat{\sigma}_0^2(\hat{\tau}_0)$, and $\hat{\sigma}_1^2(\hat{\tau}_0)$ we know that

$$P\left(c_{\alpha/2}<\frac{\left(\bar{y}_1(\hat{\tau}_0)-\bar{y}_0(\hat{\tau}_0)\right)^2}{\hat{\sigma}_0^2(\hat{\tau}_0)}\left(\hat{\tau}_0-\tau_0\right)<c_{1-\alpha/2}\right)\to 1-\alpha.$$

A 100(1 −α)% confidence interval for τ_0 can then be calculated as:

$$\left(\hat{\tau}_0-\left[c_{1-\alpha/2}\frac{\hat{\sigma}_0^2(\hat{\tau}_0)}{(\bar{y}_1(\hat{\tau}_0)-\bar{y}_0(\hat{\tau}_0))^2}\right]-1,\hat{\tau}_0-\left[c_{\alpha/2}\frac{\hat{\sigma}_0^2(\hat{\tau}_0)}{(\bar{y}_1(\hat{\tau}_0)-\bar{y}_0(\hat{\tau}_0))^2}\right]+1\right),$$

where [x] denotes the integer part of x.

A remaining issue is to determine the number of structural breaks that are present in the data. If we assume, for example, that a single break exists, as has been done in the related literature, when in reality there are multiple breaks, the model is misspecified and the break date estimate may be biased. We therefore use an iterative repartitioning procedure, discussed in Bai (1997b) and Hansen (2001), to determine the number and locations of the break dates. This procedure is implemented as follows. We start by estimating a model with a single structural break. Let the initial estimate be $\hat{T}_0$. The sample is then split into two subsamples $1, \hat{T}_0$ and $[\hat{T}_0 + 1, T]$ and we test for a single structural break within each subsample. Suppose that in both subsamples we reject the null hypothesis of no structural break and the additional estimated break dates are $\hat{T}_1$ and $\hat{T}_2$. We then test for a single structural break in the subsamples [1, $\hat{T}_1$], $[\hat{T}_1 + 1, \hat{T}_2]$ and $[\hat{T}_2 + 1, T]$. In other words, we test for a structural break in the 'new' subsamples [1, $\hat{T}_1$] and $[\hat{T}_2 + 1, T]$, as well as re-test for a structural break in, $[\hat{T}_1 + 1, \hat{T}_2]$ (which in the initial iteration yielded $\hat{T}_0$). This process of further splitting the sample and re-testing earlier break dates is repeated until the null hypothesis of no structural break cannot be rejected in any of the relevant subsamples.

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Notes

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1. Histories of the Bayh-Dole Act are in, for example, Stevens, 2004, Mowery, 2005, and Leyden and Link (2015). Important arguments in favor of alternatives to the Bayh-Dole approach are suggested in Kenney and Patton (2009).

2. Balven et al. (2018) correctly point out that studies of the Bayh-Dole Act in particular, and academic entrepreneurship in general, have focused almost exclusively on formal

mechanisms of technology transfer and have often ignored informal mechanisms. We agree with this observation and hope that our emphasis on infrastructure will provide insight into the context that influences the myriad dimensions of the technology transfer process.

3. Over the years, many universities have dropped the name Technology Transfer Office in favor of alternative names that emphasize innovation and commercialization.

4. See, https://www.autm.net/.

5. Link et al. (2007) show empirically that technologies also informally exit the university through the "back door."

6. Some might reasonably challenge this starting assumption because organizations, such as the Research Corporation, did serve as a so-called patenting agent for a number of research universities. We revisit this point in the next section of the paper and again in the concluding section of the paper.

7. Previous researchers have questioned whether the Bayh-Dole Act affected university patenting by estimating a model with a predefined structural break at 1980 (or even at 1981 to account for a lag). Whether it be the Bayh-Dole Act or other legislation, one does not know when a legislation will begin to have an effect. Our prior is to let the data define when a structural break occurred. We find from our analysis in this paper that a break date was in 1982. We do not claim that this break date was caused by the Bayh-Dole Act. Rather, the fact that the implementation of the Bayh-Dole Act and the occurrence of the break date are close in time does suggest that the Act may have been responsible for the institutionalization of university research through the formation of TTOs.

8. Our overview of the literature is brief because others have written excellent and detailed reviews of this literature.

9. Rafferty (2008), who used aggregated national university patenting data, arrived at the same conclusion as did above writers. Rafferty tempers his conclusion by noting that the Bayh-Dole Act was not the only influence on university patenting. He emphasized that the Supreme Court's decision in Diamond vs. Chakrabarty, for one example, furthered the effort of universities to patent life forms and to engage in patents related to biotechnology.

10. Perhaps Kenney (1986) was unable to foretell the Mowery (2005) view that the acceleration in patenting in the early 1980s might have occurred even in the absence of the Bayh-Dole Act because his foundational research was published in 1986, very shortly after the initiation of Bayh-Dole legislation.

11. The Research Corporation was founded in 1912, and University Patents was founded in 1974.

12. We thank an anonymous reviewer for pointing out that the advent of the technology transfer offices might also represent a fundamental institutional change at universities, where commercializing research and engagement of the university in the economy joined research and teaching as legitimate and fundamental goals of the university. This question has yet to be explored in the literature, but such investigations are needed. See also, Balven et al. (2018) for a systematic review of the technology transfer literature.

13. Regarding the start date for this time series, AUTM data show that the first U.S. TTO was established in 1925 at the University of Wisconsin at Madison.

14. The distribution theory for both the maximum Wald statistic and the break date estimator is non-standard, but has been derived by Andrews, 1993, Andrews and Ploberger, 1994 and Bai, 1994, Bai, 1997a). Additional discussion is provided below in the Appendix.

15. The estimation sample is 1925–2014 but with the conventional 15% trimming rule, which removes 15% at the start and 15% at the end of the sample, we only look for a structural break within the "middle" 70% of the observations. Thus, the Wald statistic is computed over the range 1938–2000.

16. With , the shift in the mean is estimated to have occurred in 1977. Following the convention in the literature, we call the break date (or change point), even though it is the last period leading up to the actual change.

17. We do not report results for the period [1996, 2000] because the time span is too short for a meaningful test.

18. For example, such countries are (based on our independent research along with the date of the related legislation): Austria (2002), Brazil (2004), China (1994), Denmark (1999), Finland (2007), France (1999), Germany (2002), India (2008), Indonesia (2002), Italy (2001), Japan (1999), Malaysia (2009), Mexico (2002), Norway (2003), Philippines (2009), Russia (2003), South Africa (2008), South Korea (2000), Spain (1983), and the United Kingdom (1992).

19. See footnote 12 above.

20. Hayter and Link (2018) discuss the tradeoff between publishing (an informal transfer mechanism) and patenting (a formal mechanism). Audretsch and Link (2018) discuss the role of innovation capital as one of a number of informal entrepreneurial inputs to the innovation output of commercialization.

21. The implementation of this method was initially complicated because there was no distribution theory for the test and hence, critical values were not known. A general solution to this problem—which applies to nonlinear models as well—was provided by Andrews (1993) and Andrews and Ploberger (1994), who derived approximate (asymptotic) distributions for maximum-type statistics, including those based on Wald, likelihood-ratio (LR), and Chow tests. These distribution are highly non-standard and

only a limited number of critical values have been tabulated. More recently, however, Hansen (1997) provided a convenient, simulation-based approach to calculating p-values for these tests.

22. To illustrate the testing approach, we use a model with a single structural break. The model is easily generalized to allow for multiple breaks.

23. This Wald statistic is based on least squares estimation of a linear model with a structural break. Because yt is a count variable, we also estimated a Poisson regression model with a structural break in the mean and used the likelihood ratio statistic to test for structural breaks. The estimated break dates were largely the same. However, certain periods within the sample are characterized by under- or over-dispersion, making the Poisson model less appropriate. Our preferred specification is therefore linear. The Poisson results are available on request from the authors.

24. This restricted range is used to ensure that the test has sufficient power.

25. The p-values were calculated using the approximation of Hansen (1997). His code is available at http://www.ssc.wisc.edu/~bhansen/progs/progs_stchange.html.

26. This problem has received substantial attention in the literature. For example, Hinkley, 1970, Worsley, 1986, Bhattacharya, 1987, and Yao (1987) derived approximate sampling distributions for the change-point (i.e., break date) estimator, in the context of random sampling from a parametric distribution that is subject to a structural break in its parameters. Hawkins (1986) and Bai, 1994, Bai, 1997a) derived similar results for models estimated by least squares.