Trajectory of Maturity: An Empirical Analysis of US Biofuel Innovations

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Abstract: Employing the patent data over 1977-2011, this study explores the factors determining innovative activities in the US ethanol industry. We take into account both demand-side and supply-side factors, the latter of which is represented by constructed knowledge stocks, to quantify the effects of price- and policy-induced innovations. We quantify the citation generation process using patent citations and construct the simple and weighted stocks of knowledge with weights of patent productivity. We confirm that both the supply-the demand-side factors, such as knowledge stock, crude oil price and government R&D expenditure, have positive and statistically significant effects on the technological innovations of biofuels in the United States.

Keywords: knowledge stock, patent count and citation, R&D expenditure.

JEL codes: Q16; Q42; Q48.

1. Introduction

Finite and unequal distribution of fossil fuel resources, together with growing concerns on environment, has brought significant changes to world energy production and consumption. Countries worldwide facing the issues of energy security and low carbon economy have been stimulated to seek alternative energy resources to displace fossil fuel sources. Ethanol is one successful example, which is the most widely used biofuel in the world. It has been grabbing significant attention in some countries, especially US and Brazil. These two countries accounted for about 88% of worldwide ethanol production in 2010.

The US ethanol production experienced rapid growth in the late 1970s when the subsidy established by the Energy Policy Act of 1978 launched the industry. Ethanol production has quadrupled from 3.9 billion gallons in 2005 to 13.9 billion gallons in 2011 (RFA 2012). Ethanol substituted about 10% of the U.S. gasoline supply in 2011, up from 1% in 2001. While ethanol production is expanding rapidly, however, there are also increasing concerns. For example, strong feedstock demand leads to higher crop price, intensive crop production and potentially significant land use changes as well as associated environmental impacts.

The US ethanol industry has grown into an established and mature industry, which is largely accelerated by the support policies including blending mandate, tax credit, and import tariff provided by the federal and state governments. Between 1983 and 2005, production costs of corn ethanol in the US decreased by about 65% and industrial processing costs decreased by approximately 45% (Hettinga et al. 2009; Chen and Khanna 2012). Over the same period, we see similar trend in patent granting of ethanol-related innovations. There were massive applications of patents between late 1970s and early 1980s. After a quiet development period, a large number of technological innovations with applications of new patents emerged after 2005.

This study attempts to provide a rigorous empirical understanding on the technological innovations of the US ethanol industry using patent count and citation data. Several unique features of technological innovations in the U.S. ethanol industry distinguish the present study from the existing literature. First, the booms of ethanol-related innovations of late 1970's and after 2005 are largely stimulated by not only energy price, but also national and local government policies, which is not typical for other renewable energy sectors. Contrast to the finding in Pope (2002) that government energy R&D has weak and insignificant effect, we find strong and significant impact of government R&D expenditure on ethanol innovations.

Second, as a mature industry, the development of US ethanol industry provides an interesting setting within which to examine the driving forces of innovative activities and to test the hypotheses of price- and policy- induced innovations, which is first proposed in Popp (2002). Insights into the ethanol industry will provide lessons on various aspects, e.g., capital investment and policy intervention, for the development of other renewable energy resources. Especially, technology evolution of ethanol should present valuable information on the mechanisms to stimulate renewable energy innovations in the future.

Finally, utilization of patent data by itself should be interesting. Patent count and citation information provide not only the quantity but also the scientific value of innovative output. Patent citation indicates knowledge contribution by prior research, or in other words, the usefulness of existing knowledge to later inventors. Following the method developed in Popp (2002), we construct the stocks of knowledge measuring the level of currently available technological knowledge on ethanol. It turns out that incorporating the measure of existing knowledge is important for quantifying the price and policy effects on technological innovations.

Several interesting findings emerge from our research. First, similar to the demand for knowledge, the supply of knowledge is also proved to play an important role in the innovation process as ignoring the supply factor biases estimation results. Second, although the weighted knowledge stock captures the productivity of patents, the simple knowledge stock better reflects the existing knowledge of US ethanol as a significant number of patents generated during the recent ethanol boom after 2005 have not got much chance to be cited. Finally, the empirical analysis of the determinants of technological innovation finds that both demand-side and supply-side factors, including the knowledge stock, crude oil price, and government R&D expenditure, positively and significantly affect ethanol innovations.

The rest of paper is organized as follows. Section 2 reviews the existing literature. Patent data used in the study are discussed in Section 3. In Section 4 we describe the empirical models for constructing of the knowledge stocks and for quantifying the determinants of technological innovation. Section 5 analyzes the estimation results followed by some concluding comments in the final section.

2. Literature review

A number of studies employ patent data to analyze the driving forces of technological innovations in energy and renewable energy sectors. Popp (2002) is the first study proposing the concept of knowledge stock in studying energy-related technological innovations using patent data. The study shows that (i) both energy prices and existing knowledge stock have significant positive effects on energy-efficient innovation, and (ii) omitting the quality of knowledge biases the estimates. Accounting for both domestic and international knowledge flows, Verdolini and Galeotti (2011) construct internal and external knowledge stocks to study determinants of innovation in energy technologies. Using the data of 38 innovating countries from 1975-2000,

the authors find that higher geographical and technological distances are associated with lower probability of knowledge flow.

Johnstone, Hascic and Popp (2008) examine the effects of policy incentives on the patent counts of a number of renewable energy technologies. Their sample includes 25 high-income countries that have adopted various support policies to encourage the development of renewable energies. While public policy plays a significant role in inducing innovations, the efficacy of alternative policy instruments varies by energy sources. De Freitas and Kaneko (2012) confirm a unidirectional relation from consumption to technological innovation of sugarcane ethanol in Brazil.

The studies on the innovative activities and the determinants of US ethanol are sparse. Hettinga et al. (2009) investigate technological development of US ethanol production using an experience curve approach where technological learning is identified in two separate systems: corn production and ethanol processing. Main drivers behind large cost reductions include high ethanol yields and the introduction of ethanol-specific and automated technologies. Using data on US dry-mill ethanol processing costs of 1983-2005, Chen and Khanna (2012) investigate the reasons underlying the declining processing costs. They find that (i) US corn ethanol production exhibits decreasing return-to-scale, (ii) learning-by-doing plays an important role in cost reduction, and (iii) imports of sugarcane ethanol contribute to the increasing competitiveness of the industry. The most relevant to our work is Karmarkar-Deshmukh and Pray (2009). Their results indicate the significant positive effect of oil prices and federal research grants on ethanol-related innovations. The study was conducted in 2008 and only 445 ethanol-related patents are identified and utilized. More importantly, they omit the effect of knowledge stock by assuming patents are equally important for later innovations.

3. Ethanol patent count data and descriptive evidence

In this study technological innovations in ethanol industry are represented by the number of patents registered at the US Patent and Trademark Office (USPTO). To identify the ethanol-related patents, we search the USPTO database and collect all the patents having the word "ethanol" in title or abstract. This initial search generated a total of 3,539 patents, applied over 1975 to 2011 and granted over January 1976 to June 2012. Patent descriptions were then manually reviewed and screened for its direct relevance. In our study, we focus on the ethanol patents that are related to agriculture and industrial production of ethanol, including the usage of residuals ethanol production and combustion-related patents such as ethanol engine patents. The screening yields 1,090 ethanol patents over the sample period.

Following de Freitas and Kaneko (2012), we classify the ethanol patents into five categories including agricultural feedstock production, ethanol production process, engine and ethanol combustion, ethanol by-product, and emission treatment.[1] Figure 1 presents the annual patent counts by category sorted by the application year. There are a total of 1,090 ethanol patents registered at USPTO, 673 of which are granted to US assignees.[2] We focus on US patents in this study.

As shown in Figure 1, the trend of patenting activity is largely consistent with the development of ethanol industry. Patenting activities reached its peak in early 1980s. After that total patent applications declined to around 20 patents each year. Applications grew by more

[1] De Fretas and Kaneko (2012) classify ethanol-related patents into six categories. We exclude the category of "Transport and storage" as no relevant patents in our data.

[2] An assignee and an inventor of a patent may be different in some cases because, for example, an employee could likely assign a patent to a company. But the distinction doesn't affect the patent counts and our empirical results as we limit our attention to the US assignees.

than 20% per year since 2006, which was triggered by increasing domestic ethanol demand and high crude oil prices. Different from Brazil's ethanol industry where agriculture-related patents experienced a major increase during the 2000s (de Freitas and Kaneko 2012), patenting activities are dominated by the innovations related to ethanol production followed by combustion patents in the United States.

Figure 2 illustrates the trend of ethanol patents by U.S. assignee groups from 1975 to 2011.[3] There are three assignee groups including US government, university, and private company. Over the sample period, private companies led the ethanol-related technological innovations in the US followed by universities and the government. Comparing US government and universities, Figure 2 shows that the US government was more active in patenting than universities during early 1980s. However, universities are more contributing to current ethanol boom as shown by their patenting activities since 2005. We consider the total US patents in the empirical analysis in a latter section because that as we discussed above government policies play critical roles in the development of US ethanol industry and associated innovations. Not only private companies but also university and government related research organizations are affected by the support and contribute significantly to the ethanol booms. Inclusion of all groups should paint a more complete picture of the knowledge creation and accumulation processes.

Table 1 summarizes the information on patent citations. We can see that the distribution of patent citations is highly skewed. About 38% of US patents received no citation over the whole period. 37% of the patents received between one and ten citations and 16% of patents

[3] Patents assigned to more than one assignee are counted more than once. This yields a total of 1,090 patents by assignees.

received eleven to thirty citations. The only remaining 3% of patents received thirty or more citations. On average, a patent was cited approximately seven times over the sample period.

4. Empirical methods

In this section we turn to discuss the empirical methods for (i) constructing knowledge stocks, and (ii) analyzing driving factors of technological innovations.

Knowledge Stock

Knowledge stock is a commonly applied measure to proxy the existing stock of scientific knowledge (see, e.g., Jaffe and Trajtenberg 1996; Popp 2002). Higher level of available knowledge stock indicates better technological opportunity and should push for more innovative activities in the following period. Patent citations contain useful information for knowledge stock construction. Citation to a previous patent reflects the usefulness of knowledge contained in the earlier cited patent and its knowledge contribution to the new citing patent (Popp 2002). Hence, frequent citations suggest high quality of the patent and its relatively more important contribution to knowledge accumulation of the industry.

Following Popp (2002), we use patent citations to estimate the parameters underlying the citation generation process after taking the relative importance of individual patents into account. The estimates are then combined with patent counts to construct the time-varying knowledge stocks of ethanol-related innovations.

The probability that a patent applied in year T cites a patent k granted in year t can be described by the following double-exponential function:[4]

$$p(k,K) = \alpha(k,K)\exp\left[-\beta_1(T-t)\right]\left[1-\exp(-\beta_2(T-t))\right] \tag{1}$$

[4] Eqn. (5), p. 168, Popp (2002).

where knowledge becomes obsolete at the rate of β_1 and diffuses by the rate of β_2. $\alpha(k,K)$ denotes the parameters capturing attributes of the citing or cited patents that may influence the probability of citation. The probability of citation $p(k,K)$, which is also referred as citation frequency, is defined as a function of the citation lag $(T-t)$ and the parameters.

The number of citations in a cited-citing years pair is denoted as $c_{k,K}$, cited patents granted in year t as n_t, and citing patents applied in year T as n_T. Then eqn. (1) can be rewritten as: [5,6]

$$p_{k,K} \equiv \frac{c_{k,K}}{n_t n_T} = \alpha_0 \alpha_t \alpha_T \exp\left[-\beta_1 (T-t)\right]\left[1-\exp(-\beta_2 (T-t)\right] \tag{2}$$

where the probability of citation is $p_{k,K} \equiv c_{k,K} / n_t n_T$ and $\alpha(k,K)$ incorporates the constant α_0, cited year effect α_t, and citing year effect α_T. The cited year effect α_t indicates the usefulness of the cited patents and therefore the likelihood of being cited. Hence, higher cited year effect indicates higher probability of being cited and thus reflects the relative importance of the patent.

Two types of knowledge stocks, simple knowledge stock (K_t^{simple}) and weighted knowledge stock ($K_t^{weighted}$), for year t are constructed using the estimated parameters in (2) and US patent counts as follows:

$$K_t^{simple} = \sum_{s=1980}^{t} Pat_s \exp\left[-\beta_1 (t-s)\right]\left[1-\exp(-\beta_2 (t-s))\right] \tag{3}$$

$$K_t^{weighted} = \sum_{s=1980}^{t} \alpha_s Pat_s \exp\left[-\beta_1 (t-s)\right]\left[1-\exp(-\beta_2 (t-s))\right] \tag{4}$$

[5] We excluded the observations at $t=T$ as such citation pairs are rare in our sample.
[6] Eqn. (6), P. 169, Popp (2002).

where Pat_s represents the number of patents granted in year s, α_s is the estimate of the cited year effect, β_1 and β_2 represent the estimated decay and diffusion rates, respectively. Here K_t^{simple} provides a measure of knowledge accumulation of ethanol related innovations using annual patent counts. $K_t^{weighted}$ quantifies the knowledge stock after incorporating patents' relative usefulness by using the cited year effect as a multiplicative factor. The knowledge stocks are constructed over the period of 1977-2010.

Determinants of Innovation

We proceed to analyze the determinants of technological innovations. In general, technological innovation is affected by both demand and supply factors (see Verholini and Galeotti 2011 for a more detailed discussion). The demand-side determinants are factors that make technological innovations more or less profitable for a given level of supply. Crude oil prices, public R&D and government policy indicators are considered to be the demand-side factors here.

Record high fossil fuel prices provide economic incentives to invest in renewable energy sources including biofuel. Also, the US government has been playing an important role in stimulating biofuel development in recent years by providing significant amount of R&D funding and strong policy incentives. However, the effect of government policies on technological innovations is found to be unclear in the literature. For example, in studying the innovations related to biomass for electricity, Johnstone, Hascic and Popp (2008) find that government R&D spending has a negative and significant effect on patent applications, implying that government R&D funding crowds out private spending. For US corn ethanol, Karmarkar-Deshmukh and Pray (2009) show that the research funding provided by the federal government has a positive and significant effect on technological innovations. But they also show that the tax

credit has a negative and significant effect on ethanol innovations, while the effect of mandate policy was a negative but not significant.

In the current study, the ethanol-related US patents applied in year t, Pat_t, are determined as:

$$Pat_t = \exp\left[\gamma_1 K_{t-1} + \gamma_2 P_t^E + \gamma_3 R\&D_t + \gamma_4 Policy_t + \varepsilon_t\right] \quad (5)$$

where K_{t-1} is one-year lagged simple (or weighted) knowledge stock of year $t-1$. P_t^E is annual imported crude oil price deflated by consumer price index. $R\&D_t$ denotes the real expenditure (in 2005 dollars) for renewables R&D conducted by the US Department of Energy. $Policy$ is the policy indicator for federal government ethanol policy, mainly the Renewable Fuel Standard (RFS), and ε_t stands for unobservable errors with mean zero. We use the two policy proxy variables: (i) a dummy variable that takes the value of one since 2006 indicating the presence of RFS (named "EPA Dummy"), and (ii) annual renewable fuel volume mandate under the RFS since 2006 (named "RFS Quantity").

5. Analysis of the results

First, we discuss the results on citation generation process specified in eqn. (2) and the knowledge stock construction in eqns. (3) and (4). We use data on ethanol patents granted over 1977-2010 for the cited patents (k). The citing patents (K) are the patents that cite patents in the set of k and are sorted by application year over 1978-2011. A total of 6,989 pairs are included after sorted by cited-citing year pairs. Eqn. (2) is then estimated using nonlinear least squares method. As it is difficult for the estimates to converge with separate α_t and α_T for each cited-

citing year, we group the cited-citing years into 2-2 year intervals assuming that α_t and α_T are constant over the intervals, but different across the intervals.

Table 2 shows the estimation results where the cited and citing years are grouped into 2-2 year intervals, respectively. When we normalize $\hat{\alpha}_{t=1977-1978} = 6.54$ to one, the interpretation of estimated values of $\hat{\alpha}_t$ becomes relative to the base years. For example, the estimate of $\hat{\alpha}_{t=1981-1982} = 4.47/6.54 = 0.68$ means that the likelihood for a patent issued in 1981-1982 to receive a citation is about 32% lower than that of a patent issued in 1977-1978. In Table 2, the cited year effects $\hat{\alpha}_t$ is decreasing over 1977-2010, while the citing year effects $\hat{\alpha}_T$ is increasing over 1978-2011. This is intuitively reasonable in that the earlier patents are granted, the higher chances patents have to be cited. Likewise, the later patents are applied, the higher chance patents cite other patents. This is also consistent with the probability of citation $p_{k,K} \equiv c_{k,K} / n_t n_T$, presented in Figure 3 where $p_{k,K}$ is high before 1980, stable between 1980 and 2005, and increasing quickly after 2005. The higher probability of citation before 1980 is captured by higher cited year effects, and the higher probability of citation after 2005 is reflected into higher citing year effects.

Figure 4 plots the constructed simple and weighted stocks over the period of 1977-2010. Both simple and weighted knowledge stock reached the peak in mid-1980s. While weighted knowledge stock has declined after that, simple knowledge stock shows upward trend since 2005, reflecting the current increasing number of ethanol patent application. As pointed out in Popp (2002), the falling value of the citation-weighted knowledge stock suggests the deteriorating quality of knowledge represented by the patents over time, or decreasing rate of return of obsolete patents. Given the fact that the recent ethanol-related innovation boom happened after

2005, in such a short period newly granted patents don't have much chance to be cited. We argue that the simple knowledge stock provides a better and more complete picture of the existing knowledge of ethanol industry.[7]

Time series of the variables included in the determinants estimations are presented in Figure 5 and the corresponding descriptive statistics are reported in Table 3. Except the concave shape of weighted knowledge stock, real crude oil prices and government R&D expenditure show consistent evolution with the patenting activities over time. Peaks of patent application appeared during the periods of around 1980 and after 2005, together with relatively high crude oil prices and government expenditure on renewable energy research. Eqn. (5) is estimated using a Negative Binomial (NB) model as the evidence of over-dispersion of patent counts by the Lagrange Multiplier (LM) test rejects a Poisson model.

Government R&D expenditure is considered to be endogenous as it could be determined by some factors influencing patenting activities. We seek valid instrument variables (IVs) to deal with the endogeneity issue, which should influence R&D but be independent of the patent generation. Following the literature (e.g., Jaffe 1986; Barro 1998), we instrument the government R&D with GDP growth rate because that R&D expenditure should respond to exogenous productivity growth. Figure 5 indicates a clear relationship between government R&D and GDP growth rate that in both early 1980s and after 2005, high government R&D responded to low GDP growth rate and they were all stable over a long period before 2005.

To address the endogeneity concern of knowledge stock, we applied the method in Popp (2002) by using the time trend, lagged GDP and lagged oil price as instrumental variables for

[7] This is also reflected by the empirical analysis of innovation determinants, which we will discuss in a latter section.

both simple and weighted knowledge stocks. In the estimation of the NB regression, we explore a two-stage procedure where the government R&D and knowledge stock variables are instrumented. In the first stage, endogenous variables are regressed on chosen IVs. The predicted values of the first stage regression are then used as regressors in a second stage of NB model. The standard errors are obtained using bootstrapping method. The first stage regression results are summarized in the lower panel of Table 4.

The upper panel of Table 4 presents the estimation results of eqn. (5) where the coefficient estimates are reported as incidence rate ratios.[8] Specifications with simple knowledge stock (Columns I and II) are the best fitted models indicated by the high log likelihood values and χ^2 test statistics. The results show positive and statistically significant effects of one-year lagged simple knowledge stock, crude oil prices, and government R&D expenditure on the technological innovations of US ethanol industry. Specifically, one unit increase in the simple knowledge stock is associated with about 2.5%-2.6% increase of number of ethanol patents; one unit increase in the crude oil price increases the probability of innovation by about 2.3%-2.5%; one unit increase in the government R&D increases the probability of innovation by 0.9%. Both policy proxies (EPA dummy and RFS volume mandate) have positive impact on patenting activities but not significant. This is reasonable because that (i) the policies are implemented after 2005, which shares the same upward trend with crude oil price and government R&D

[8] The estimates are transformed from $\hat{\beta}$ to $\exp(\hat{\beta})$ together with standard errors. $\hat{\beta}$ can be interpreted as the estimated rate ratio for a one unit increase in the explanatory variable $X_{\hat{\beta}}$ holding the other variables constant. In other words, if the level of $X_{\hat{\beta}}$ increases by one unit, the rate for patents would be expected to change by a factor of $\hat{\beta}$ (increases if $\hat{\beta} > 1$ or decreases if $\hat{\beta} < 1$) (Stata Corporation 2001).

expenditure, and (ii) the policy effects are largely captured by the government renewable energy R&D expenditure although it is not clear to us the structure of that expenditure.

Columns III-IV report NB regression results using weighted knowledge stock. The knowledge stock and policy variables are not found to be an important technology-push factor. It is not surprising because that as we discussed above weighted knowledge stock declined over the sample period, which is dominated by the decreasing return to innovation and failed to capture the recent ethanol boom since 2005. The last two columns present the results omitting the knowledge stock variable. Most of the results are similar to the first two columns except the negative impact (estimated coefficient less than one) of RFS mandate.

6. Conclusion

Employing the patent counts and citations data of ethanol-related technologies, this study extends the analysis of technological innovation to the US ethanol industry, which has grown to a matured industry with intensive government support through federal and state policies as well as R&D funding.

Following the literature, this study incorporates the effect of knowledge accumulation by quantifying the citation generation process and constructing the knowledge stocks of existing technology. The empirical analysis of the determinants of technological innovation finds that both supply- and demand-side factors, including simple knowledge stock, crude oil price, and government R&D funding, positively and significantly affect ethanol innovations. The policy effect is not significant after controlling the factors listed above.

Our research suggests the need for future research in the following areas. First, availability of more satisfactory variables to proxy the demand-side factors such as policies and private R&D expenditure would further strengthen the results in the paper. Second, it would be

interesting to examine how the geographic characteristics of patent counts and citations differ significantly across assignee groups. Third, as Brazil is the second largest ethanol producing country in the world, it would generate meaningful policy discussion if we can extend the study to the sugarcane ethanol innovations in Brazil.

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Table 1. Ethanol patents granted to US assignees, January 1976-June 2012.

Total US Patents	673
Citations	# (%)
0	255(38%)
1-10	252(37%)
11-20	105(16%)
21-30	38(6%)
>30	23(3%)
Max	91
Cited patents	418 (62%)
Average citation/patent	7.07

Table 2. Regression result for probability of being cited for US patents
(Standard errors are in the parentheses)

Variable	Estimates	Variable	Estimates
Cited Year Effects α_t		Citing Year Effects α_T	
1977-1978	6.54*** (0.72)	1978-1979	0.69 (0.70)
1979-1980	6.52*** (0.40)	1980-1981	0.39 (0.37)
1981-1982	4.47*** (0.43)	1982-1983	0.25 (0.22)
1983-1984	3.76*** (0.53)	1984-1985	0.25 (0.21)
1985-1986	2.72*** (0.55)	1986-1987	0.31 (0.24)
1987-1988	1.85*** (0.49)	1988-1989	0.38 (0.26)
1989-1990	1.35*** (0.44)	1990-1991	0.57 (0.36)
1991-1992	0.85** (0.33)	1992-1993	0.80* (0.45)
1993-1994	0.59** (0.27)	1994-1995	1.17** (0.59)
1995-1996	0.47* (0.25)	1996-1997	1.92** (0.83)
1997-1998	0.33 (0.20)	1998-1999	1.94*** (0.73)
1999-2000	0.25 (0.17)	2000-2001	2.47*** (0.78)
2001-2002	0.16 (0.12)	2002-2003	3.26*** (0.85)
2003-2004	0.13 (0.11)	2004-2005	4.49*** (0.91)
2005-2006	0.10 (0.08)	2006-2007	6.48*** (0.97)
2007-2008	0.05 (0.05)	2008-2009	8.80*** (1.08)
2009-2010	0.09 (0.09)	2010-2011	15.74*** (1.28)
Decay (β_1)		0.24*** (0.03)	
Diffusion (β_2)		8.98*** (0.004)	
Constant (α_0)		0.001 (0.001)	

Note: Single (*), double (**), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3. Descriptive statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Patents	33	20.67	15.74	3	58
Weighted Stock	33	16.11	16.65	1.23	54.12
Simple Stock	33	46.76	19.69	2.37	83.64
GDP (billion $)	33	92.63	25.89	56.73	132.06
GDP Growth Rate (%)	33	2.75	2.09	-3.07	7.19
Oil Price ($/barrel)	33	48.16	23.72	16.97	98.61
Government R&D (hundred millions $)	33	58.92	53.29	19.28	219.06

Table 4. Regression results for determinants of innovation
(Bootstrapping standard errors are in the parentheses)

Variable	I	II	III	IV	V	VI
Lagged Simple Stock	1.026***	1.025***				
	(0.005)	(0.004)				
Lagged Weighted Stock			1.008	1.004		
			(0.01)	(0.008)		
Oil Price	1.023***	1.025***	1.025***	1.028***	1.024***	1.025***
	(0.005)	(0.003)	(0.007)	(0.006)	(0.004)	(0.004)
Government R&D	1.009***	1.009***	1.026***	1.024***	1.020***	1.020***
	(0.004)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
EPA dummy	1.264		1.158		1.060	
	(0.35)		(0.57)		(0.24)	
RFS quantity		1.005		0.985		0.974
		(0.02)		(0.05)		(0.03)
Log likelihood	-104.51	-105.17	-117.95	-117.94	-104.58	-104.21
χ^2	1712.43	1743.06	468.72	480.84	946.18	545.98
First stage regression	R&D	Simple Stock	Weighted Stock			
GDP Growth Rate	-9.83**					
	(4.21)					
Time trend		7.16**	2.88			
		(2.76)	(1.79)			
Lagged GDP		-2.55**	-1.53**			
		(1.01)	(0.66)			
Lagged Oil Price		0.19	0.14			
		(0.15)	(0.10)			
Constant	85.94***	-14011.97**	-5602.76			
	(14.48)	(5409.45)	(3512.80)			
R-squared	0.15	0.20	0.60			
F statistics	5.44	2.32	13.77			

Note: Single (*), double (**), and triple (***) asterisks denote significance at the 0.10, 0.05, and 0.01 levels, respectively.

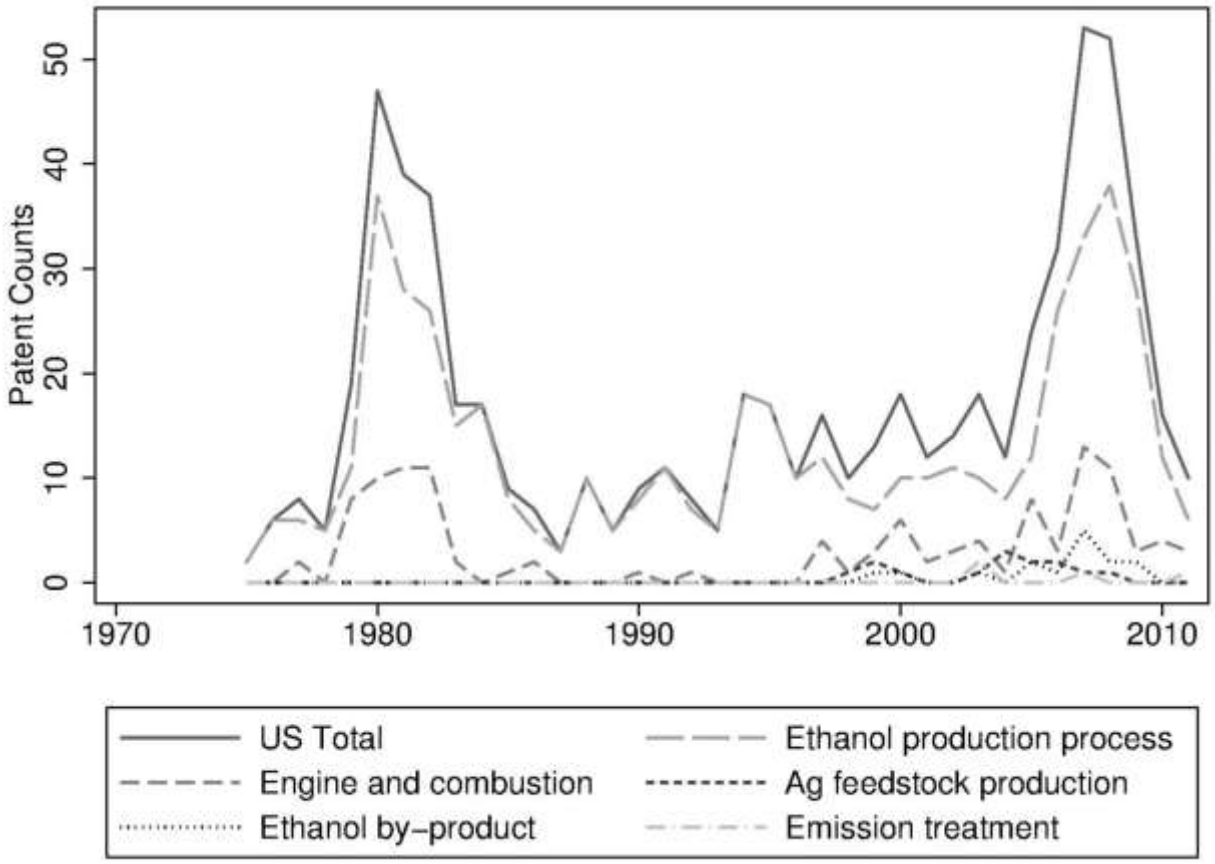

Figure 1. Annual Ethanol Patent Counts by Category, 1975-2011.

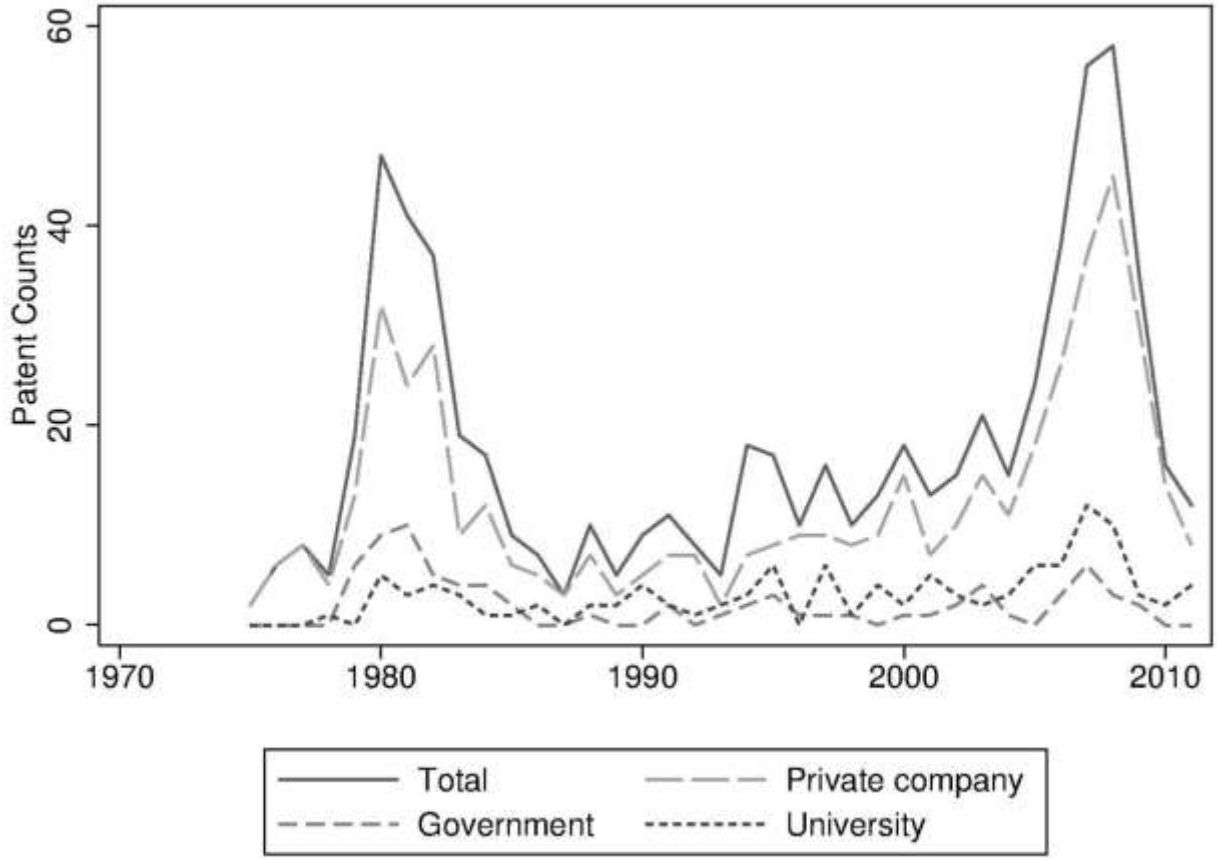

Figure 2. Annual U.S. Ethanol Patent by Assignee, 1975-2011.

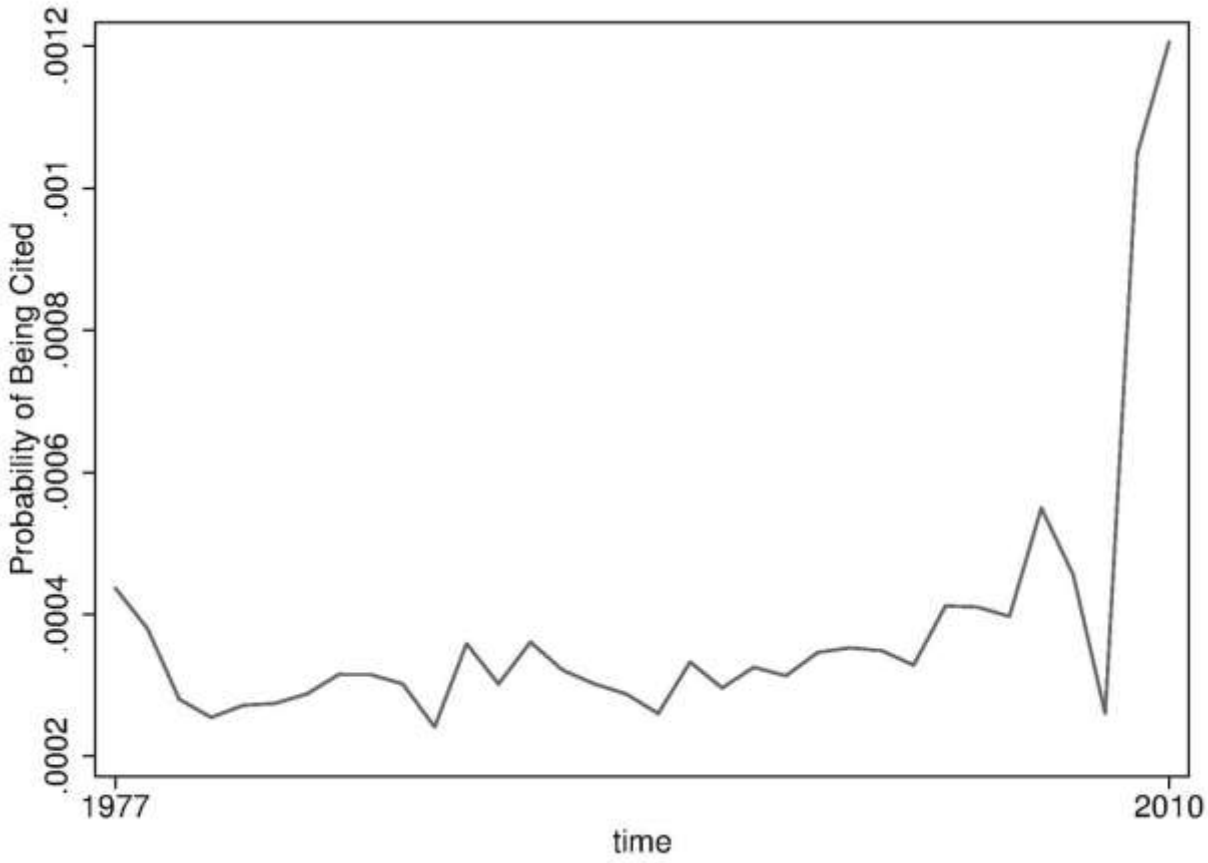

Figure 3. Average probability of being cited by patent grant year, 1977-2010

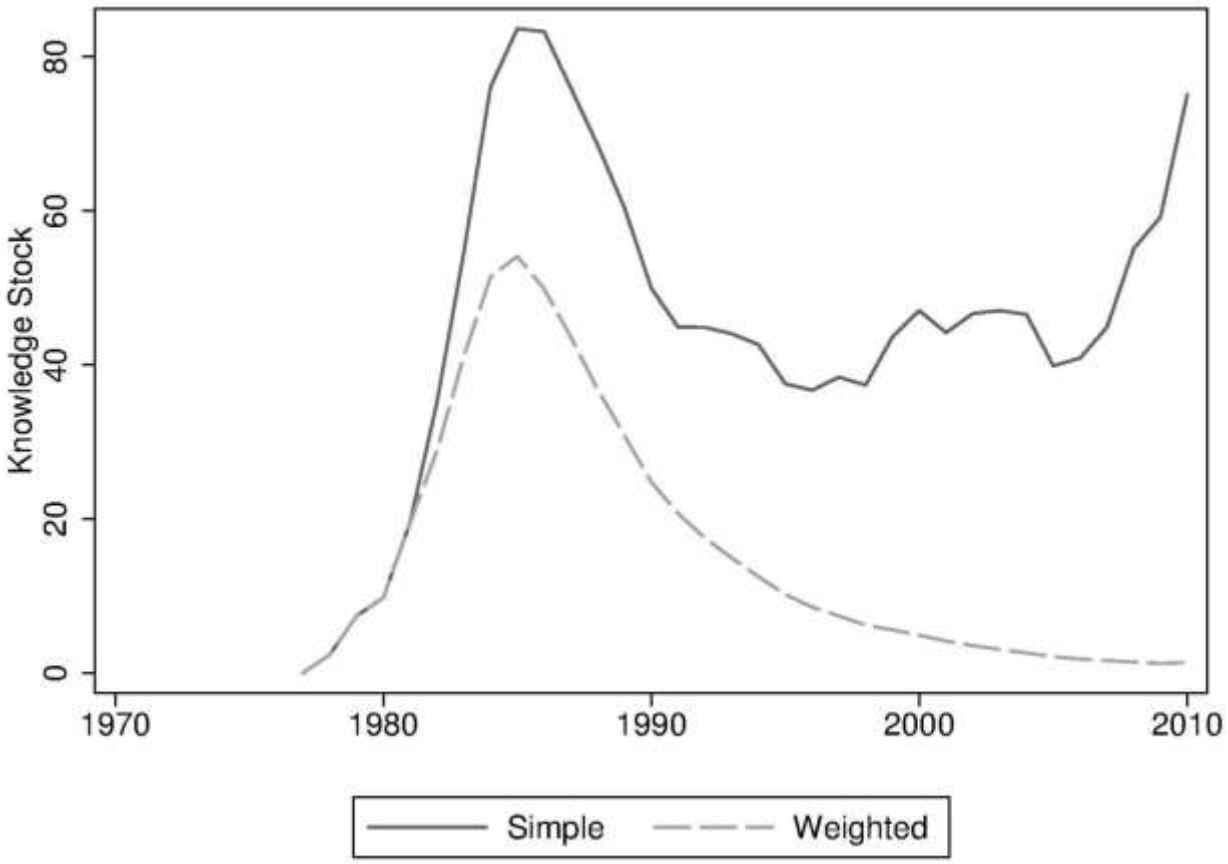

Figure 4. Knowledge Stocks, 1977-2010

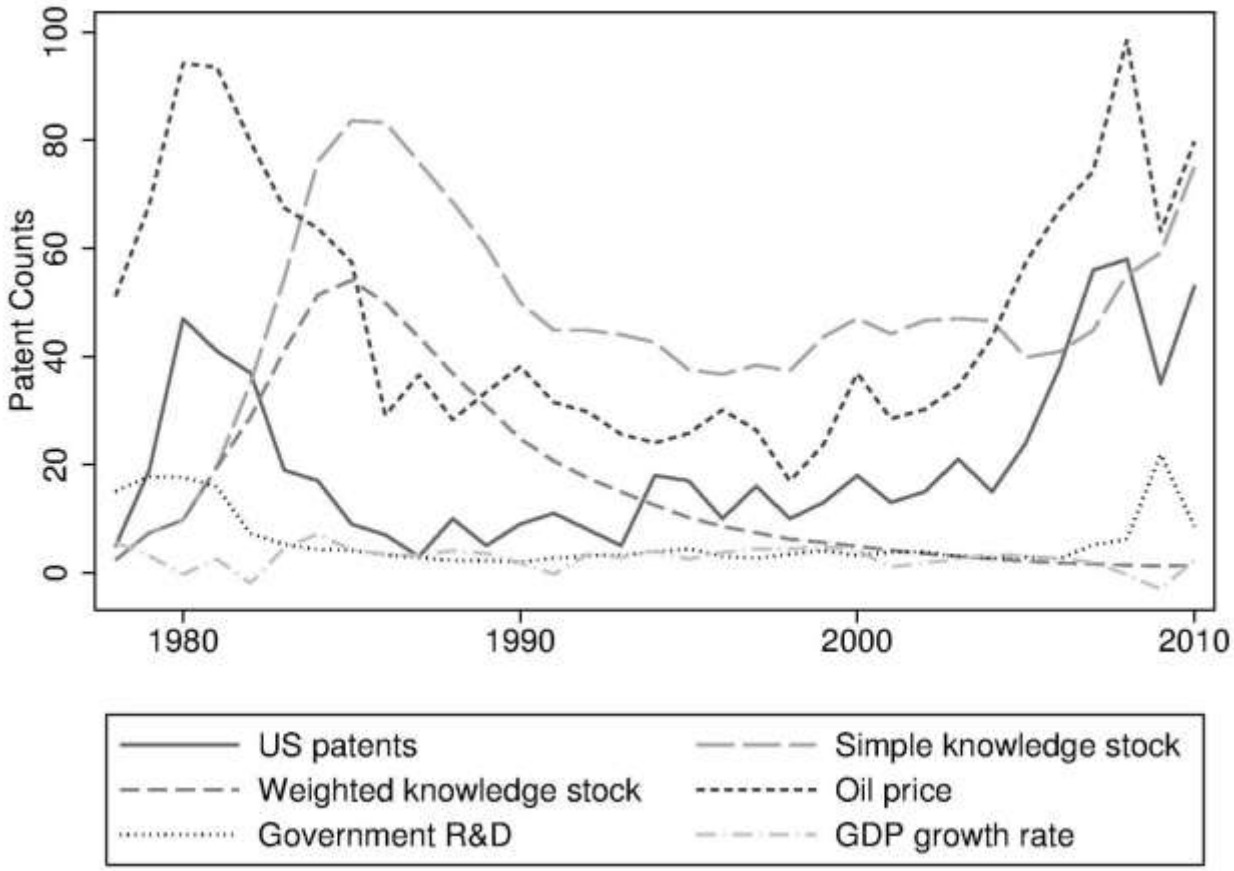

Figure 5. Time series of variables, 1978-2010.