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Price- and Policy-Induced Innovations: The Case of U.S. Biofuel

Heesun Jang and Xiaodong Du

Using patent counts and citation data from 1977 to 2011, we explore the determining factors of innovative activities of the U.S. biofuel industry. We take into account both demand-side factors—such as crude-oil price, government R&D expenditure on biofuel, and federal-level support policies—and supply-side factors, represented by constructed knowledge stocks, to quantify the effects on biofuel-related innovations. The citation generation process is quantified using patent citation records and the estimates are used to construct the simple and weighted stocks of knowledge with weights of patent productivity. We confirm that both the demand and supply factors have positive and statistically significant effects on technological biofuel innovations in the United States.

Key words: knowledge stock, patent count and citation, R&D expenditure

Introduction

Finite and unequal distribution of fossil fuel resources, together with growing environmental concerns, have caused significant changes to world energy production and consumption. Countries worldwide facing issues of energy security and low carbon economies have been stimulated to seek alternative energy resources to displace fossil fuel sources. Ethanol, a biofuel, is the most widely used of these alternative energy sources in the world. It has grabbed significant attention in some countries, including the United States and Brazil, which accounted for about 88% of worldwide ethanol production in 2010.

U.S. ethanol production experienced rapid growth in the late 1970s after a subsidy established by the Energy Policy Act of 1978 launched the industry. Domestic ethanol producers were also protected from Brazilian competitors by the import tariff beginning in the 1980s.[1] From 2005 to 2011, ethanol production quadrupled from 3.9 billion gallons to 13.9 billion gallons. As of 2012, ethanol substituted about 10% of the U.S. gasoline supply (Renewable Fuels Association, 2012). Substantial expansion of ethanol production and resulting feedstock demand have raised some concerns about increasing crop prices, intensive corn production, and potentially significant land use changes as well as associated environmental impacts.

The growth of the U.S. ethanol industry has largely been accelerated by federal and state government support policies. Major recent federal-level support policies include

1. The blending mandate, which was established by the Renewable Fuel Standard (RFS) in 2005 and further expanded by the Energy Independence and Security Act of 2007. The mandate requires that a minimum amount of ethanol be blended into fuel gasoline each year;

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[1] The original federal support policies were revised by later legislation, but the basic structure of tax and import tariffs remained in place until the end of 2011 (see MacDonald and California Energy Commission, 2004, for a more detailed discussion).

2. A tax credit of $0.45/gallon for ethanol blenders;
3. An import tariff of $0.54/gallon.

Since the tax credit and import tariff expired at the end of 2011, the U.S. ethanol industry has grown into an established and mature industry. Production costs of corn ethanol dropped by about 65% and industrial processing costs decreased by approximately 45% between 1983 and 2005 (Hettinga et al., 2009; Chen and Khanna, 2012). Over the same period, we see an upward trend in patents granted for ethanol-related innovations. There was a massive group of patent applications between the late 1970s and early 1980s. After a quiet development period, new patent applications for technological innovations rose again after 2005.

In general, technological innovations are pushed forward by both demand and supply factors (see Verdolini and Galeotti, 2011, for a more detailed discussion). Supply-side factors refer to changes that affect existing knowledge or potential opportunities for future inventive activities. Demand-side factors make new innovations more or less profitable for a given level of existing knowledge. This study attempts to provide a rigorous empirical understanding of the determinants of technological innovations in the U.S. ethanol industry. Several unique features of the U.S. biofuel innovations motivate this study.

First, the biofuel innovation booms that occurred in the late 1970s and after 2005 are largely stimulated by both demand-side and supply-side factors, including oil prices, R&D expenditures, government policies, and existing knowledge. Similar to previous findings (e.g., Popp, 2002), we find that oil prices and existing knowledge have a strong and significant impact on biofuel innovations.

Second, the U.S. ethanol industry provides an interesting setting within which to examine the driving forces of innovative activities and to test the hypotheses of induced innovations first proposed by Popp (2002). Insights into the ethanol industry will provide lessons on various aspects of the development of other renewable energy resources, such as capital investment and policy intervention. In addition, the evolution of ethanol technology should present valuable information on developing mechanisms to stimulate future renewable energy innovations.

Finally, using patent data by itself should be interesting. Patent counts and citations provide information about not only the quantity but also the scientific value of innovative output. Patent citations indicate knowledge contribution by prior research, or the usefulness of existing knowledge to later inventors. Following Popp (2002), we construct the stocks of knowledge measuring the level of current technological knowledge on ethanol, which is considered as the supply-side determining factor of biofuel innovations. Incorporating the measure of existing knowledge is important for quantifying price and policy effects.

Our contribution to the literature is threefold. First, we confirm that not only does the demand for knowledge innovation and accumulation play an important role in the innovation process, but the supply-side factor represented by the existing knowledge stock does as well. Second, both simple and weighted knowledge stocks reflect existing knowledge of U.S. ethanol and have positive and significant impact on ethanol innovations. Finally, empirical analysis of the innovation determinants finds that both demand and supply factors positively and significantly affect ethanol innovations.

Literature Review

A number of studies employ patent data to analyze driving forces of technological innovations in energy and renewable energy sectors. Popp (2002) first proposed using knowledge stock to study energy-related innovations using patent data. The study shows that both energy prices and existing knowledge stock have positive and significant effects on energy-efficient innovations and that ignoring quality of the knowledge biases the estimates. Accounting for both domestic and international knowledge flows, Verdolini and Galeotti (2011) constructed internal and external knowledge stocks to study determinants of innovation in energy technologies. Using data from thirty-eight innovating countries from 1975 to 2000, they found that larger geographical and technological distances are associated with lower probabilities of knowledge flows.

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

Studies on the innovative activities and the determinants of U.S. ethanol innovations are sparse. Hettinga et al. (2009) investigated technological development of U.S. ethanol production using an experience curve approach in which 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 automated technologies. Using data on U.S. dry-mill ethanol processing costs from 1983 to 2005, Chen and Khanna (2012) investigated the reasons underlying declining processing costs and found that U.S. corn ethanol production exhibits decreasing return-to-scale, learning-by-doing plays an important role in cost reduction, and imports of sugarcane ethanol contribute to increasing competitiveness of the domestic industry.

Karmarkar-Deshmukh and Pray (2009) found that oil prices and federal research grants had significant positive effects on ethanol-related innovations. The study was conducted in 2008 and identified and utilized 445 ethanol-related patents. However, they assumed that patents are equally important for later innovations and did not account for the effect of knowledge stock.

The U.S. government has played an important role in stimulating biofuel development in recent years by providing significant amounts of R&D funding and strong policy incentives. However, the effect of government policies on technological innovations is not found to be clear in the literature. For example, in studying innovations related to biomass for electricity, Johnstone, Hascic, and Popp (2008) found 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 U.S. corn ethanol, Karmarkar-Deshmukh and Pray (2009) showed that research funding provided by the federal government has a positive and significant effect on technological innovations, but they also show that the ethanol tax credit has a negative and significant effect on ethanol innovations, while the effect of the mandate policy was negative but insignificant.

Ethanol Patent-Count Data and Descriptive Evidence

This study uses the number of patents registered at the U.S. Patent and Trademark Office (USPTO) to represent ethanol-related technological innovations. To identify these patents, we searched the USPTO database and collected patents with the word "ethanol" in the title or abstract. The initial search generated a total of 3,539 patents that were applied for from 1975 to 2011 and granted from January 1976 to June 2012. Patent descriptions were then manually reviewed and screened for direct relevance. The screening yielded 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.[2] Figure 1 presents the annual patent counts by category sorted by application year. There were a total of 1,090 ethanol patents registered at

[2] We exclude the transport and storage category included in de Freitas and Kaneko (2012), as there are no relevant patents in the U.S. data.

Table 1. Ethanol Patents Granted to U.S. Assignees, January 1976–June 2012

Total U.S. Patents	673
Cited patents	418 (62%)
Average citations per patent	7.07
Citations	**# (%)**
0	255 (38%)
1–10	252 (37%)
11–20	105 (16%)
21–30	38 (6%)
>30	23 (3%)
Max	91

USPTO, 673 of which were granted to U.S. assignees and are the focus of the current study.[3]

As shown in figure 1, the trend of patenting activity is largely consistent with the development of the U.S. ethanol industry. Patent applications reached a peak in early 1980s and declined to around twenty each year after that. Applications grew by more than 20% per year after 2005, which was largely triggered by increasing domestic ethanol demand and high crude-oil prices. Unlike Brazil's ethanol industry, in which agriculture-related patents experienced a major increase during the 2000s (de Freitas and Kaneko, 2012), patenting activities in the United States are dominated by innovations related to ethanol production and engines/combustion.

Figure 2 illustrates the trend of ethanol patents by U.S. assignee groups from 1975 to 2011.[4] There are three assignee groups, including the government (at both the federal and state level), universities, and private companies. Over the sample period, private companies led the ethanol-related technological innovations, followed by universities and the government. The U.S. government was more active than universities in patenting during early 1980s, but universities contributed more to the post-2005 ethanol boom. We consider total U.S. patents in the latter analysis because government support policies played a critical role in the development of U.S. ethanol industry and related technological innovations. Private companies as well as universities and government-related research organizations are significantly affected by extensive government support and have made important contributions to ethanol-related knowledge accumulation. Including patents from all groups paints a more complete picture of the knowledge creation and accumulation processes.

Table 1 summarizes the information on patent citations, the distribution of which is highly skewed. About 38% of U.S. patents received no citation over the whole sample period, while 37% of patents received one to ten citations and 22% received eleven to thirty citations. Only the remaining 3% received thirty or more citations. On average, each patent has been cited approximately seven times over the past thirty-seven years.[5]

Empirical Methods

Knowledge Stock

Knowledge stock is a commonly applied measure of the existing stock of scientific knowledge (see Jaffe and Trajtenberg, 1996; Popp, 2002). A higher level of existing knowledge stock indicates better

[3] An assignee and an inventor of a patent may be different in some cases. One explanation may be that, for example, it is more likely for an employee to assign a patent to a company. For patents with U.S. assignees (which are the focus of our study), over 90% of inventors are resident in the United States. We therefore do not make a distinction between assignee and inventor, as it has little effect on patent counts or the empirical results of our analysis.

[4] Patents assigned to more than one assignee are counted multiple times, for a total of 1,090 patents by assignees.

[5] A significant number of patents are applied and granted toward the end of the sample period and did not have time to generate as many citations as earlier patents. This may have some implications for the estimates of the citation generation process explained in a later section.

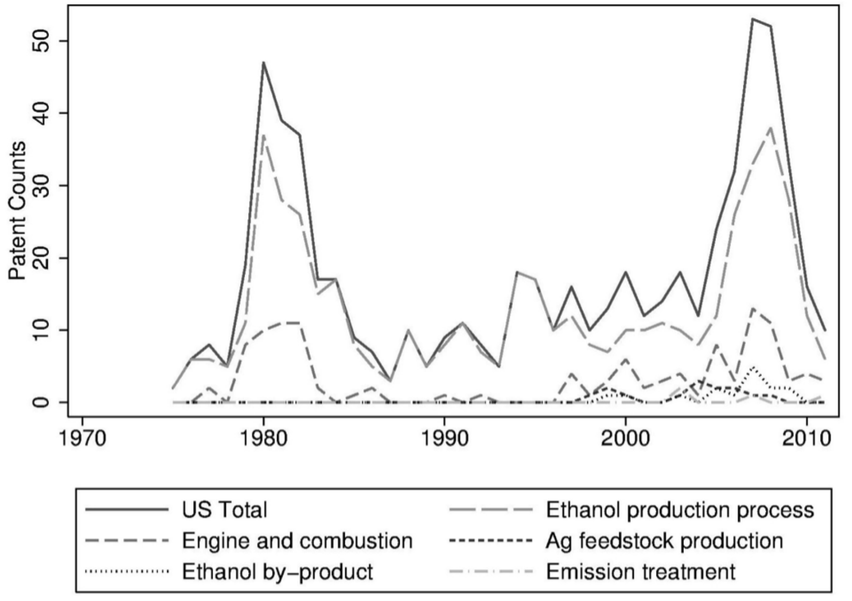

Figure 1. Annual Ethanol Patent Counts by Category, 1975–2011

technological opportunities that should push forward more innovative activities in the future. Patent citations contain useful information for constructing knowledge stock. Citing a previously granted patent reflects the usefulness of the cited patent and its knowledge contribution to the new, citing patent (Popp, 2002). Frequent citations suggest that the cited patent is of high quality and has made important contributions to knowledge accumulation in the industry.

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

The probability that a patent applied for in year T cites a patent k granted in year t can be described by the following double-exponential function:[6]

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

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

The number of citations in a cited-citing year pair is denoted as $c_{k,K}$, cited patents granted in year t as n_t, and citing patents applied for in year T as n_T. Equation (1) can be rewritten as [7,8]

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

where $\alpha(k,K)$ in equation (1) 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. A higher cited year effect

[6] Equation (5) (p. 168 Popp, 2002).
[7] Equation (6) (p. 168 Popp, 2002).
[8] We exclude the observations at the year when $t = T$, as such citation pairs are rare in the data.

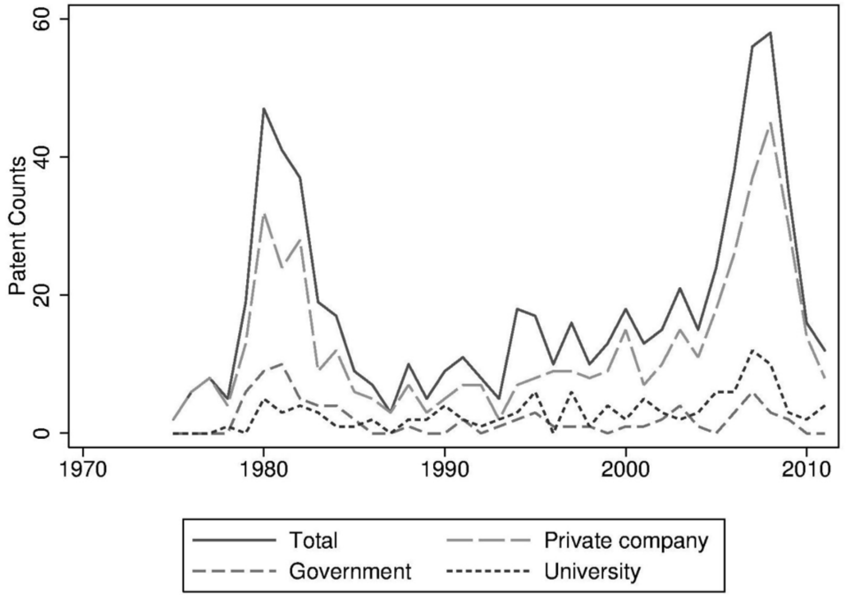

Figure 2. Annual U.S. Ethanol Patents by Assignee Group, 1975–2011

indicates a higher probability of being cited and thus reflects the relative importance of the cited patent.

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

$$K_t^{simple} = \sum_{s=1980}^{t} Pat_s \exp[-\hat{\beta}_1(t-s)][1-\exp(\hat{\beta}_2(t-s))]; \tag{3}$$

$$K_t^{weighted} = \sum_{s=1980}^{t} \hat{\alpha}_s Pat_s \exp[-\hat{\beta}_1(t-s)][1-\exp(\hat{\beta}_2(t-s))]; \tag{4}$$

where Pat_s represents the number of patents granted in year s, $\hat{\alpha}_s$ is the estimated cited year effect, and $\hat{\beta}_1$ and $\hat{\beta}_2$ represent the estimated decay and diffusion rates. The simple knowledge stock, K_t^{simple}, provides a measure of existing knowledge accumulation of ethanol using annual patent counts. The weighted knowledge stock, $K_t^{weighted}$, quantifies the knowledge stock after incorporating patents' relative usefulness by using the cited year effect as a multiplicative factor. Both knowledge stocks are constructed over the period of 1977–2010.

Determinants of Innovation

The constructed knowledge stocks are included to represent the supply-side factor. Crude-oil prices, government R&D expenditure on biofuel, and support policy indicators are considered to be demand-side factors.

Ethanol-related U.S. patents applied for in year t, Pat_t, are determined as[9]

$$Pat_t = \exp[\gamma_1 K_{t-1} + \gamma_2 P_t^E + \gamma_3 R\&D_t + \gamma_4 Policy_t + \varepsilon_t], \tag{5}$$

[9] There exists a strong relation between product market competition and innovation (see, e.g., Aghion et al., 2005). This study assumes a perfectly competitive biofuel market and does not account for the possible impact of market structure on innovations.

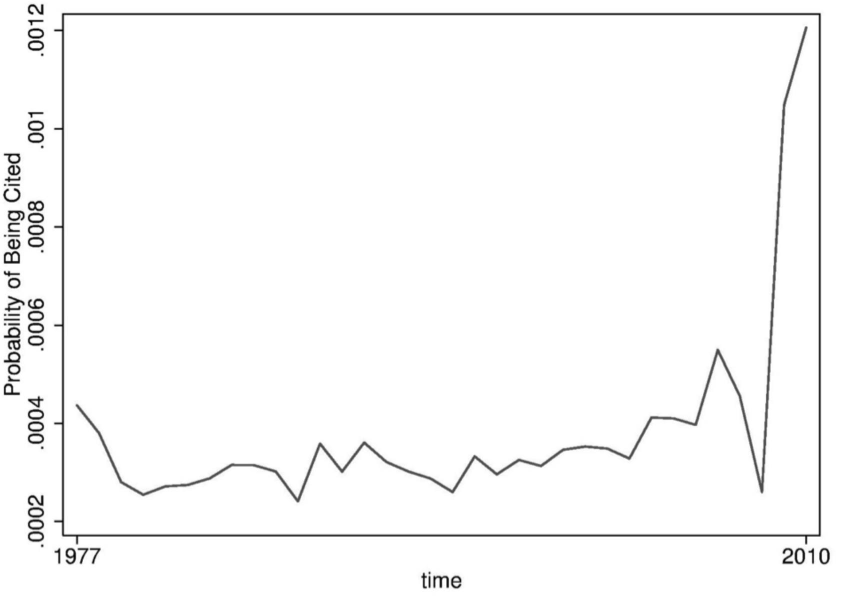

Figure 3. Average Probability of Being Cited by Patent Grant Year, 1977–2010

where K_{t-1} is the lagged simple (or weighted) knowledge stock for year $t-1$ and P_t^E is the annual imported crude-oil price deflated by consumer price index. $R\&D_t$ denotes the real government R&D expenditure on biofuel (in 2012 dollars).[10] $Policy_t$ is the policy indicator for the major ethanol support policies of the U.S. federal government after 2005, and ε_t stands for unobservable errors with zero mean. We use two policy proxy variables: (i) a dummy variable that takes the value of 1 for 2006 and after indicating the presence of major ethanol support policies (named "policy dummy") and (ii) annual volume mandate of ethanol under the RFS (and revised RFS2) since 2006 (named "RFS mandate"). We assume that policies take effect one year after establishment. While the "RFS mandate" mainly attempts to pick up the effect of the blending mandate, the "policy dummy" captures the aggregate effect of all existing federal support policies.

Analysis

First, we discuss the results of the citation generation process specified in equation (2) and the knowledge stock construction in equations (3) and (4). We use ethanol patents granted over 1977–2010 for the cited group, k. Citing patents, K, are those that cite patents in the group of k and are sorted by the application years of 1978–2011. A total of 6,989 pairs are included after sorting by the cited-citing years. Equation (2) is then estimated using a nonlinear least squares method with White's heteroskedasticity-consistent standard errors (White, 1980).[11] It is difficult for the estimates to converge with separated parameters α_t and α_T for each cited-citing year, therefore we group the cited-citing years into three-by-three-year intervals, assuming that α_t and α_T are constant over the three years within the interval but can vary across intervals.

[10] The data are part of the government energy technology R&D budget collected by the International Energy Agency (IEA) and can be downloaded from the IEA website http://www.iea.org/statistics/RDDonlinedataservice/. We thank an anonymous reviewer for pointing this out. The database also includes R&D budgets for other renewable energy resources, including solar and wind, which are used as instrumental variables in a later section.

[11] In equation (2), each observation is the average probability of citation for an individual cohort, (i.e., average of a group of patents). These averages tend to be more accurate for larger groups. A potential heteroskedasticity problem exists, which is why we apply the heteroskedasticity-consistent estimator. The authors thank an anonymous reviewer for pointing this out.

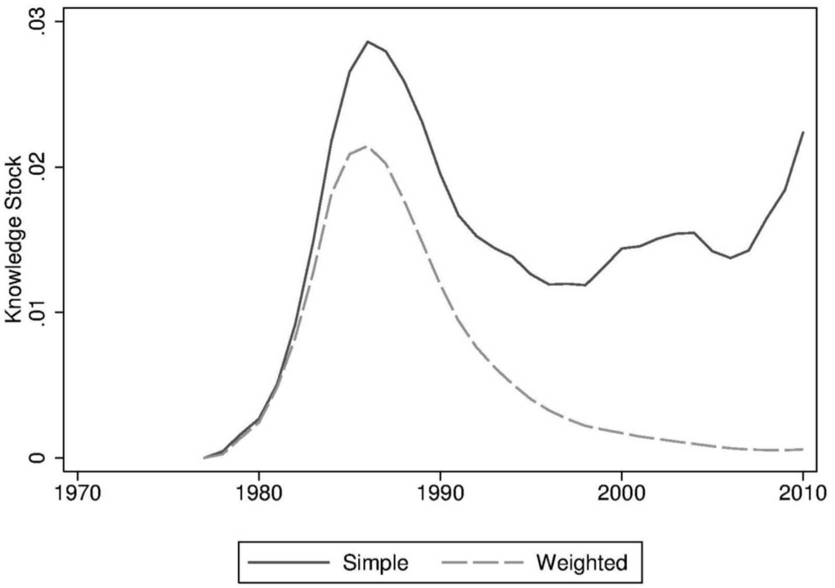

Figure 4. Constructed Knowledge Stocks, 1977–2010

Table 2 reports the estimation results of the citation generation process. If we normalize the estimated cited year effect in the initial year of 1977, $\hat{\alpha}_{1977} (= 3.97)$, to 1, the estimated values of a later year, $\hat{\alpha}_t$, can be interpreted as relative to the base year. For example, the estimate of $\hat{\alpha}_{1978-1980}$ becomes $1.78 (= 7.08/3.97)$, which means that the likelihood for a patent issued in 1978–1980 to receive a citation is about 78% higher than that of a patent issued in 1977. The cited-year effects $\hat{\alpha}_t$ decrease over 1978–2010, while the citing-year effects $\hat{\alpha}_T$ increase over 1982–2011 (table 2). This is reasonable given that earlier granted patent have a higher chance of being cited. Likewise, after the earlier ethanol boom, the later a patent was applied for, the higher chance it cites other earlier granted patents. This is also consistent with the probability of citation $(p_{k,K} \equiv c_{k,K}/n_t n_T)$, which is calculated from data and presented in figure 3. The citation probability was high before 1980, stable between 1980 and 2005, and increased significantly after 2005. The relatively higher probability of citation before 1980 is captured by the higher cited-year effects, and that after 2005 is reflected in higher citing-year effects, as a significant number of citations are generated by new patent applications during the recent ethanol boom. Both the estimated decay rate of $\beta_1 (= 0.42)$ and the diffusion rate of $\beta_2 (= 0.0002)$ are of comparable magnitude to those in Popp (2002), where the estimates are 0.353 and 0.00199, respectively.

Figure 4 plots the constructed simple and weighted knowledge stocks over the period of 1977–2010. Both knowledge stocks reached a peak in mid-1980s. While weighted knowledge stock declines after that, simple knowledge stock shows an upward trend after 2005, which indicates a significant increase in recent ethanol-related innovations. The falling value of weighted knowledge stock suggests either deteriorating quality of the knowledge represented by patents over time or a decreasing rate of return of research (Popp, 2002).

Time series of the variables included in the estimation of innovation determinants are presented in figure 5, and table 3 reports the corresponding descriptive statistics. Except the concave shape of the weighted knowledge stock, real crude-oil prices and government biofuel R&D expenditure show consistent patterns with patenting activities over time. Peaks of patent applications appear around 1980 and after 2005, together with relatively high crude-oil prices and government R&D

Table 2. Regression Results for Probability of Being Cited for U.S. Patents

Variable	**Estimates**	**Variable**	**Estimates**
Cited-Year Effects α_t		Citing-Year Effects α_T	
1977	3.97**	1978	5.01
	(1.81)		(8.47)
1978–1980	7.08***	1979–1981	1.09
	(1.09)		(1.62)
1981–1983	5.67***	1982–1984	0.44
	(0.58)		(0.54)
1984–1986	4.19***	1985–1987	0.44
	(1.04)		(0.54)
1987–1989	1.99**	1988–1990	0.57
	(0.84)		(0.62)
1990–1992	1.41*	1991–1993	1.08
	(0.85)		(0.96)
1993–1995	0.82	1994–1996	1.75
	(0.64)		(1.23)
1996–1998	0.53	1997–1999	2.82*
	(0.51)		(1.47)
1999–2001	0.34	2000–2002	3.45***
	(0.39)		(1.24)
2002–2004	0.20	2003–2005	4.44***
	(0.26)		(0.89)
2005–2007	0.13	2006–2008	8.17***
	(0.20)		(0.89)
2008–2010	0.16	2009–2011	15.92***
	(0.27)		(3.50)
Decay rate (β_1)	0.42***		
	(0.07)		
Diffusion rate (β_2)	0.0002		
	(0.0003)		
Constant (α_0)	1.49***		
	(0.0001)		
R squared	0.53		

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels. Numbers in parentheses are standard errors.

Table 3. Descriptive Statistics, 1978–2010

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Patents	33	20.67	15.74	3	58
Weighted Knowledge Stock	33	24.97	27.43	1	85.11
Simple Knowledge Stock	33	33.95	15.36	1	63.71
Deflated Oil Price ($/barrel)	33	48.16	23.72	16.97	98.61
Biofuel R&D (million $)	33	145.25	239.25	0.74	1235.02

Notes: Simple and weighted knowledge stocks are normalized using 1978 as the base year (i.e., both stocks in 1978 are equal to 1).

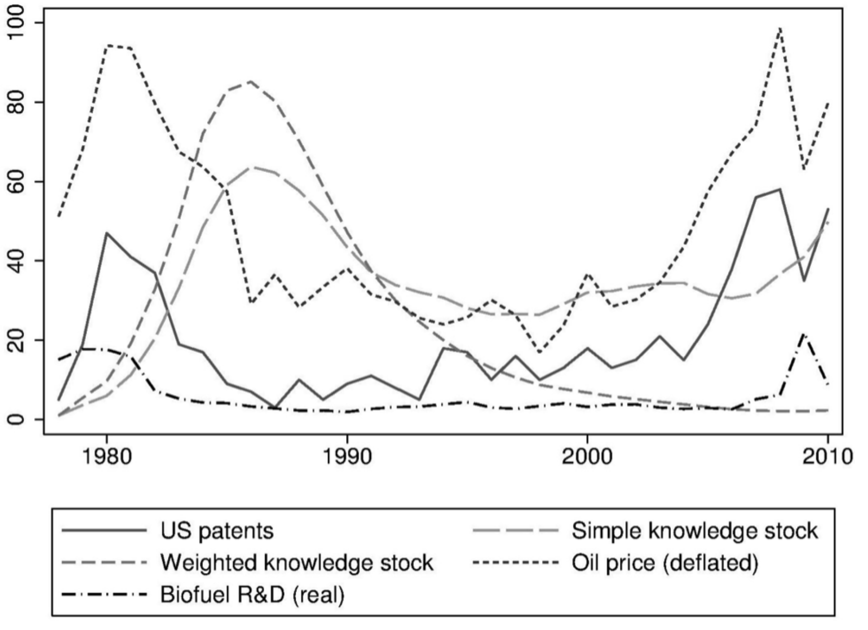

Figure 5. Time Series of Included Explanatory Variables, 1978–2010

Notes: Simple and weighted knowledge stocks are normalized using 1978 as the base year. Biofuel R&D expenditures (in $10 million) are deflated to 2012 dollars.

expenditure. Equation (5) is estimated using a Negative Binomial (NB) model because the Lagrange Multiplier (LM) test of over-dispersion rejects the Poisson model.

Government R&D expenditure on biofuel is considered to be endogenous in this setting because it could be potentially determined by some other factors influencing patenting activities at the same time. To deal with the endogeneity issue we rely on valid instrument variables (IVs), which must be directly related to biofuel R&D expenditure but affect patent generation only through R&D. We use government R&D expenditures on wind and solar energy as the instrumental variables because it is reasonable to assume that government funding decisions for various renewable sources (such as wind, solar and biofuel) are closely correlated and that government R&D expenditures on wind or solar have not had an effect on innovative activities for biofuel.[12] The first-stage regression results are summarized in the lower panel of table 4, which confirm the validity of the chosen IVs.

To address the endogeneity concern of knowledge stocks, following Popp (2002), we use a time trend and lagged GDP as instrumental variables for both simple and weighted knowledge stocks. In the NB regression, we explore a two-stage procedure. In the first stage, the endogenous biofuel R&D expenditure and knowledge stocks are regressed on the chosen IVs and other exogenous variables, including oil price. The predicted values of the first-stage regression are then used as regressors in the second-stage NB regression. The standard errors are obtained using the standard bootstrapping method.[13]

[12] We thank an anonymous reviewer for suggesting the IVs. As discussed above, the government expenditures for wind and solar energy are also obtained from the IEA website.

[13] The first-stage regression results for the knowledge stocks presented in the lower panel of table 4 indicate that the IVs are weak given the relatively low values of the F statistics, especially for the simple knowledge stock. As a robustness check, we run the NB regressions without instrumenting the knowledge stock. The results are largely consistent with those reported in columns I–IV of table 4, except that the estimated coefficients on the weighted knowledge stock are positive but not statistically significant at the 10% level.

Table 4. Regression Results for Determinants of Innovation

Variable	I	II	III	IV	V	VI
Lagged Weighted Stock	0.022***	0.030***				
	(0.006)	(0.008)				
Lagged Simple Stock			0.040***	0.041***		
			(0.004)	(0.004)		
Oil Price	0.039***	0.031***	0.028***	0.027***	0.052*	0.052***
	(0.008)	(0.01)	(0.004)	(0.005)	(0.006)	(0.005)
Biofuel R&D	0.023	0.027*	0.008	0.007	0.025*	0.021
	(0.02)	(0.015)	(0.007)	(0.008)	(0.013)	(0.013)
RFS Mandate	0.024		0.018		−0.102*	
	(0.12)		(0.048)		(0.053)	
Policy Dummy		0.977		0.33		−0.67
		(0.72)		(0.39)		(0.49)
Log Likelihood	−123.64	−122.34	−101.63	−100.27	−135.19	−135.96
χ^2	300.83	881.49	1888.70	1238.52	359.14	307.09
First-Stage Regression	**Biofuel R&D**	**Weighted Stock**	**Simple Stock**			
Wind R&D	6.19***					
	(1.12)					
Solar R&D	−1.02***					
	(0.23)					
Oil Price	0.26	−0.11	−0.07			
	(0.16)	(0.19)	(0.13)			
Lagged GDP		−1.77	−1.25			
		(1.35)	(0.91)			
Time Trend		2.85	3.47			
		(3.67)	(2.47)			
Constant	−8.60	−5492.23	−6777.01			
	(6.89)	(7201.69)	(4847.94)			
R-squared	0.56	0.48	0.15			
F Statistics	12.27	8.75	1.60			

Notes: Simple and weighted knowledge stocks are normalized using 1978 as the base year. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels. Numbers in parentheses are bootstrapping standard errors.

The upper panel of table 4 presents the estimation results of equation (5). Columns I and II (III and IV) report the estimation results for including the lagged weighted (or simple) knowledge stock, which is omitted in columns V and VI. As expected, the results indicate positive and statistically significant effects of one-year-lagged weighted (or simple) knowledge stock and crude-oil prices on technological innovations in the U.S. ethanol industry. Furthermore, it is necessary to incorporate the knowledge stock as a supply-side factor. Biofuel R&D expenditures and policy variables are not found to be important technology-push factors, except that the coefficient of biofuel R&D in column II is statistically significant at the 10% level. Expressing the estimated coefficients as incidence-rate ratios (for the specification in column I),[14] we find that a one-unit increase in weighted knowledge stock is associated with an approximately 2.2% increase in the number of ethanol patents, a one-unit increase in crude-oil price increases the probability of innovation by about 4.0%, and a one-unit increase in government R&D expenditure increases the probability of innovation by 2.3%.

We notice the difference between the two policy variables that the RFS mandate variable attempts to capture the effect of blending mandate only, the annual dummies after 2006 account for the effect of all ethanol support policies implemented through the period. But the support policies only exist by the end of the sample period, which are co-incident with high crude-oil prices and government R&D expenditures; the policy effect may therefore be partially captured by other variables.

Conclusion

This study extends the analysis of induced innovation by using patent counts and citation data for ethanol-related technologies in the U.S. biofuel industry, which has grown to maturity through intensive federal and state government support policies as well as R&D funding.

Following the literature, we incorporate the effect of knowledge accumulation by quantifying the citation generation process and constructing existing knowledge stocks. The empirical analysis of the determinants of technological innovation finds that both supply and demand factors—including knowledge stocks and crude-oil price—positively and significantly affect ethanol-related innovations.

Our research suggests the need for future research in several areas. First, availability of more satisfactory variables to proxy the demand-side factors such as policies and private R&D expenditure on biofuel would further strengthen our analysis. Second, it would be interesting to examine how the geographic characteristics of patent counts and citations differ across assignee groups. Third, extending the study to sugarcane ethanol innovations in Brazil, the second largest ethanol producing country, would generate meaningful policy discussions.

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[14] The estimates are transformed from $\hat{\beta}$ to $\exp(\hat{\beta})$ together with standard errors, where $\hat{\beta}$ 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 $\hat{\beta}$ (increase if $\hat{\beta} > 1$ or decrease if $\hat{\beta} < 1$) (Stata Corporation, 2001). This is implemented using the –irr option in the STATA command. Results are available from the authors upon request.

References

Aghion, P., N. Bloom, R. Blundell, R. Griffith, and P. Howitt. "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics* 120(2005):701–728.

Chen, X., and M. Khanna. "Explaining the Reductions in U.S. Corn Ethanol Processing Costs: Testing Competing Hypotheses." *Energy Policy* 44(2012):153–159.

de Freitas, L. C., and S. Kaneko. "Is There a Causal Relation between Ethanol Innovation and the Market Characteristics of Fuels in Brazil?" *Ecological Economics* 74(2012):161–168.

Hettinga, W. G., H. M. Junginger, S. C. Dekker, M. Hoogwijk, A. J. McAloon, and K. B. Hicks. "Understanding the Reductions in U.S. Corn Ethanol Production Costs: An Experience Curve Approach." *Energy Policy* 37(2009):190–203.

Jaffe, A. B., and M. Trajtenberg. "Flows of Knowledge from Universities and Federal Laboratories: Modeling the Flow of Patent Citations over Time and across Institutional and Geographic Boundaries." *Proceedings of the National Academy of Sciences of the United States of America* 93(1996):12,671–12,677.

Johnstone, N., O. Hascic, and D. Popp. "Renewable Energy Policies And Technological Innovation: Evidence Based On Patent Counts." NBER Working Paper #13760, National Bureau of Economic Research, 2008.

Karmarkar-Deshmukh, R., and C. E. Pray. "Private Sector Innovation in Biofuels in the United States: Induced by Prices or Policies?" *AgBioForum* 12(2009):141–148.

MacDonald, T., and California Energy Commission. "Ethanol Fuel Incentives Applied in the U.S.: Reviewed from California's Perspective." CEC Staff Report P600-04-001, California Energy Commission, Sacramento, CA, 2004. Available online at http://www.energy.ca.gov/reports/2004-02-03_600-04-001.PDF.

Popp, D. "Induced Innovation and Energy Prices." *American Economic Review* 92(2002):160–180.

Renewable Fuels Association. "Ethanol Industry Statistics." 2012. Available online at http://www.ethanolrfa.org/pages/statistics.

Stata Corporation. *STATA Feference Manual: Release 7.* College Station, TX: Stata Press, 2001.

Verdolini, E., and M. Galeotti. "At Home and Abroad: An Empirical Analysis of Innovation and Diffusion in Energy Technologies." *Journal of Environmental Economics and Management* 61(2011):119–134.

White, H. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48(1980):817–838.