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**Biofuels Policy and Innovation Impacts: Evidence from Biofuels and Agricultural Biotechnology Patent Indicators**

Kelly P. Nelson, North Carolina State University [kpnelson@ncsu.edu](mailto:kpnelson@ncsu.edu)  
Zachary S. Brown, North Carolina State University [zsbrown2@ncsu.edu](mailto:zsbrown2@ncsu.edu)  
Lee Parton, Boise State University [leeparton@boisestate.edu](mailto:leeparton@boisestate.edu)

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# Biofuels Policy and Innovation Impacts: Evidence from Biofuels and Agricultural Patent Indicators

Kelly P. Nelson, Zachary S. Brown, Lee Parton

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## Introduction

Multiple policies have encouraged the use of biofuels, ethanol and diesel primarily derived from plant-based sources, for transportation. The majority of research and development (R&D) related to the production of these products are performed by multi-product conglomerates. This study explores if policies encouraging the use of biofuels have increased innovation related to their production. We also investigate the relationship between biofuels innovation and innovation in agricultural biotechnology, a field of research closely related to biofuels and typically of interest to the same firms. In addition to determining if policies increase biofuels innovation, we test if these policies have impacted R&D effort toward agricultural biotechnology. Finally, we check if effort toward biofuels has a positive externality to agricultural biotechnology in the form of basic scientific insights.

Previous empirical studies on the effects of energy policy on alternative energy have not focused on biofuels. Clancy and Moschini (2017) performed a theoretical analysis of ethanol mandates and innovation but their study does not test whether these policies in fact induced innovation. The literature related to biofuels policy has primarily focused on the success of these policies in their stated goals, which were primarily the reduction of fossil fuel imports and a decrease in carbon dioxide emissions. Other research has looked at indirect effects such as food prices and land use. Our research also contributes to this literature on the impacts of biofuels policy on agricultural markets by investigating the effects on agricultural R&D. This paper adds a theoretical model of firm R&D allocation with multiple products. We empirically test the impact of biofuels policy on the allocation of goods toward both biofuels and agricultural biotechnology.

We consider the effects of a comprehensive set of biofuels policies using private-sector patent indicators and policy data from 21 countries, mainly OECD members. We use patent indicators related to R&D effort and R&D output. We find that ethanol blend mandates have a significant positive effect on biofuels patenting and a significant negative effect on

some agricultural patenting. We also find that these mandates have a positive effect on quality-adjusted research output related to biofuels but not a significant impact on agricultural research output. The latter effect suggests the possibility that effort directed toward biofuels has positive spillovers into agricultural research output, as the policies significantly reduced resources directed toward agricultural research but firms were able to maintain the same level of effective R&D output. In addition, other policies also had significant positive or negative effects on either biofuels or agricultural technology patenting.

The findings are relevant for the implementation of future biofuels policies designed to stimulate demand, such as the recent decision in the United States to increase the maximum ethanol blend allowed during summer months. The finding that firms redirect resources toward the good that has demand stimulated by a policy and away from other technologies in their research portfolio is important when considering the effects of other policies that will impact firms that allocate their research resources across multiple technologies. While innovation in one area may be stimulated, it can come at the cost of innovation toward other domains.

While this paper considers a wide range of policies, we focus on innovation in only two fields, biofuels and agricultural biotechnology. We do not consider the impact on R&D in automotive and mechanical engineering or the pesticide and fertilizer technology categories, other areas in which firms research biofuels perform research. While previous economic studies of patenting have approximated the monetary value of more rudimentary patent indicators such as citation counts and of some composite metrics (Lanjouw and Shankerman 2002), the market value of the more comprehensive quality metrics used in this study are not as established in the literature.

## **Multi-Product Firms and the Innovation Decision**

Hicks argues for a theory of “induced innovation,” where “the change in a relative price of a factor is itself a spur to innovation.” (Hicks 1932, pp 124-125) Macroeconomic approaches to innovation often treat the introduction of new technologies and goods as part of an endogenous growth process driven either by growth through learning by doing, where aggregate productivity depends on levels of capital investment, or expanding varieties, where either a taste for a variety of consumer items or competition between suppliers of intermediate goods drives growth (Judd 1985; Romer 1987, 1990; Aghion and Howett 1992; Barro and Sala-i-Martin 1995). Microeconomic approaches to R&D strategies have emphasized firms’ efforts to maximize profits via cost-saving innovations, particularly when competing with other firms (Kamien and Schwartz 1972, 1974, 1976; Loury 1979; Lee and Wilde 1980; Reinganum 1982).

Innovation spillovers occur when research efforts in one field have an impact on related technological fields through complementarities in the research and development (R&D) process. Applied research intended to develop production technologies for immediate use also advances basic science (Stokes, 2011). There can be transfer of knowledge from researchers on one project to another within the same firm. These insights can inform further applied

research in the same field or in different fields. Less abstractly, resources used for research in one field could be used concurrently for other projects. This can include use of buildings for multiple laboratories or use of lab equipment and facilities across research teams. Throughout this paper, we use the term “spillover effect” to refer to these complementarities in R&D production. Figure (1) graphically depicts a model of this process using the biofuels industry as an example.

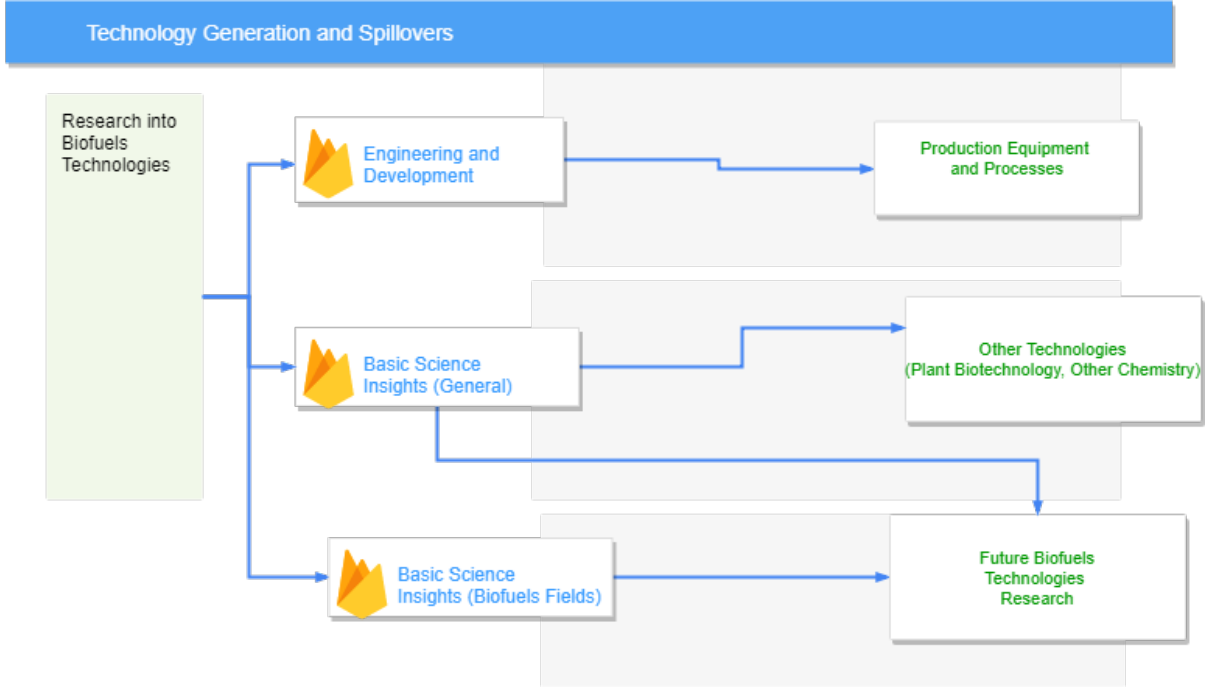


Figure 1: The Knowledge Spillover Mechanism

The firms we consider are primarily interested in generating technology. To formalize the notion of R&D spillovers, consider the following model. Firms obtain revenues either directly through producing goods using their inventions or through licensing technologies to other firms. A firm can produce differentiated good  $Y_i$  from the set  $Y_1, Y_2, \dots, Y_N$ . The firm’s total profit is shown in equation (1). The firm uses available information to determine the optimal level of output each market, then determines the optimal level of R&D resources to expend developing technology to produce each good prior to the production phase.

$$\Pi = \sum_{i=1}^N \pi_i \quad (1)$$

We combine aspects of the the Spence (1984) R&D model and the Griliches (1992) knowledge spillover model to present a multi-good cost-reduction model with the potential for technological spillovers. The firm seeks to minimize costs subject to a R&D budget constraint  $\bar{x}$ . Each technology investment  $x_i$  reduces costs for production of good  $i$ . If there are spillovers, investment in  $x_i$  will also yield  $s_{ji}x_i$ , which reduces costs for good  $j$ .

Equation (2) illustrates the nonlinear program for the firm's cost-minimization problem for the case of two goods. The costs  $c_i(Y_i, r)$  and  $c_j(Y_j, r)$  represent the costs at given output levels for each good  $Y_i$ . Costs are increasing as output levels  $Y_i$  and in the output cost parameter  $r$  representing rental rate of capital or cost of other non-R&D inputs. For simplicity, assume that the price parameter for R&D is  $w$  regardless of which good is being researched, but that R&D costs are convex and monotonically increasing.

We add restrictions to the spillover parameters. It is the case in our model that  $0 \leq s_{ij} \leq 1$  and  $0 \leq s_{ji} \leq 1$ . This means that R&D directed toward production of good  $i$  can not have a greater impact on cost-saving technology for producing good  $j$  and vice-versa. This does preclude the potential for serendipitous breakthroughs that have greater impact outside of the initial field of the research, such as the discoveries of polytetrafluoroethene resin ("Teflon") or penicillin's antibiotic properties during experiments on other subjects. However, it is intuitive to model the impacts of R&D projects as having the greatest impact with its intended field. Other parameters are restricted only to the set of non-negative real numbers.

$$\mathcal{L} = (1 - x_i - s_{ij}x_j)c_i(Y_i, r) + (1 - x_j - s_{ji}x_i)c_j(Y_j, r) - \lambda[w x_i^2 + w x_j^2 - \bar{x}] \quad (2)$$

In the case where  $s_{ij} = s_{ji} = 0$ , where research directed toward each technology has no impact on the other, the terms  $s_{ij}x_j$  and  $s_{ji}x_i$  drop out. The first-order conditions from equation (2) can then be solved to generate the equations demonstrating optimal levels of  $x_i$  and  $x_j$  with no spillover parameters. These are shown in equation (3) and (4).

$$x_i^* = \left[ \left( \frac{\bar{x}}{w} \right) \left( \frac{c_i(Y_i, r)^2}{c_i(Y_i, r)^2 + c_j(Y_j, r)^2} \right) \right]^{1/2} \quad (3)$$

$$x_j^* = \left[ \left( \frac{\bar{x}}{w} \right) \left( \frac{c_j(Y_j, r)^2}{c_i(Y_i, r)^2 + c_j(Y_j, r)^2} \right) \right]^{1/2} \quad (4)$$

In the absence of spillovers, the comparative statics are given in equation (5).

$$\frac{\partial x_i^*}{\partial \bar{x}} > 0; \frac{\partial x_i^*}{\partial w} < 0; \frac{\partial x_i^*}{\partial Y_i} > 0; \frac{\partial x_i^*}{\partial Y_j} < 0 \quad i \neq j \quad (5)$$

The change in  $x_i^*$  and  $x_j^*$  with respect to a change in the output cost parameter  $r$  depends on the functional forms of the cost functions and the relative magnitude of the  $c_i(Y_i, r)$  and  $c_j(Y_j, r)$ . If both are linear in  $r$ , then  $r$  can be factored out in the numerator and denominator and drops out of the equation, resulting in  $\frac{\partial x_i^*}{\partial r} = \frac{\partial x_j^*}{\partial r} = 0$ . If the impact on the cost of good  $i$  is greater than the impact on the cost of good  $j$ , then an increase in  $r$  will have a positive impact on  $x_i^*$  and a negative impact on  $x_j^*$ .

When we allow  $s_{ij}$  and  $s_{ji}$  to take values other than zero, the presence of the spillover parameter makes determining the effects of a change in output levels less straightforward. The general equations for  $x_i^*$  and  $x_j^*$  are given by (6) and (7) respectively.

$$x_i^* = \left(\frac{\bar{x}}{w}\right)^{1/2} \left( \frac{[c_i(Y_i, r) + s_{ji}c_j(Y_j, r)]^2}{[c_i(Y_i, r) + s_{ij}c_j(Y_j, r)]^2 + [c_j(Y_j, r) + s_{ij}c_i(Y_i, r)]^2} \right)^{1/2} \quad (6)$$

$$x_j^* = \left(\frac{\bar{x}}{w}\right)^{1/2} \left( \frac{[c_j(Y_j, r) + s_{ij}c_i(Y_i, r)]^2}{[c_j(Y_j, r) + s_{ij}c_i(Y_i, r)]^2 + [c_i(Y_i, r) + s_{ji}c_j(Y_j, r)]^2} \right)^{1/2} \quad (7)$$

While the partial derivatives with respect to  $w$  and  $\bar{x}$  retain their signs, the possible values of the spillover parameters are necessary for analysis of how changes in  $Y_i$  and  $Y_j$  impact optimal R&D levels. For  $\frac{\partial x_i^*}{\partial Y_i} > 0$ , it is necessary that  $s_{ij}s_{ji} - 1 < 0$ . For  $\frac{\partial x_i^*}{\partial Y_j} > 0$ , it is necessary  $s_{ij}s_{ji} - 1 > 0$ . Since we have restricted these parameters such that  $0 \leq s_{ij} \leq 1$  and  $0 \leq s_{ji} \leq 1$ , we can conclude that  $\frac{\partial x_i^*}{\partial Y_i} \geq 0$  and  $\frac{\partial x_i^*}{\partial Y_j} \leq 0$ . In the case in which R&D effort directed toward either good produces an equal gain in the technology level both goods,  $s_{ij} = s_{ji} = 1$ , then  $\frac{\partial x_i^*}{\partial Y_i} = \frac{\partial x_j^*}{\partial Y_j} = 0$ . In this unusual case, the goods are perfect substitutes in terms of cost reduction, and the optimal allocation of research effort is  $x_i^* = x_j^* = \sqrt{\frac{\bar{x}}{2w}}$ .

The spillover parameters  $s_{ij}$  and  $s_{ji}$  are treated as fixed for the purposes of this paper, meaning that policies will not affect them. However, it is important to consider how changes in these spillover parameters impact the optimal level of R&D for each good. When considering  $x_i^*$ , the parameter  $s_{ij}$  indicating how much investment in the other good  $x_j$  will spill over to cost reduction for good  $i$  will have a negative impact. Increases in  $s_{ji}$ , the amount of spillover from  $x_i$  into cost reduction for good  $j$  will raise  $x_i^*$ .

The cross-partials  $\frac{\partial^2 x_i^*}{\partial Y_j \partial s_{ij}}$  and  $\frac{\partial^2 x_i^*}{\partial Y_j \partial s_{ji}}$  depend on the levels of the spillovers and the level of cost for each good. For certain ranges of the spillover parameters, higher spillovers from good  $i$  onto good  $j$  or vice-versa can either aggravate or attenuate the downward force an increase in  $Y_j$  will place on  $x_i^*$ .

Government research agencies and university researchers also perform R&D but are motivated by a more diverse set of objectives than firms. These motivations include attracting funding and increasing departmental budgets, prize money, career mobility, and prestige. These motivations are not easily incorporated into a single objective function. We therefore treat commercial and non-commercial innovation separately in our analysis. Our empirical emphasis is on the commercial response to policies, which is more directly impacted by demand and supply-side policy.

## Environmental and Energy Policy Impacts on Innovation

Demand side policies, such as purchase support, border measures, or mandates, can lead to enhanced demand and therefore larger profit gains from productivity-enhancing innovations (Popp 2002, Johnstone 2010, Calel et al 2016). Policies can also change the incentives for innovation through supply-side incentives, including subsidies or tax credits for research and development. These supply side policies decrease the cost of R&D, incentivizing investment in research activities.

The literature on environmental policy-induced innovation has examined policies aimed at reducing specific forms of pollution, such as nitrogen dioxide and sulfur dioxide (Popp 2006) or chlorine (Popp et al 2011), policies incentivizing research into specific forms of alternative energies such as wind (Nemet 2009; Dechezleppêtre and Glachant 2014; Lindman and Söderholm), and policies targeting multiple forms of alternative energy technologies (Johnstone et al 2010).

Policies that encourage or mandate the use of renewable sources do so by altering the production decision for firms. Firms choose to innovate when the expected gains from an innovation, namely the decrease in production costs, outweigh the cost of developing a new technology. Since a decrease in production cost depends both on the magnitude of the per-unit cost reduction and the total output, higher equilibrium quantities can increase the incentive to reduce per-unit cost. Because of this, products with higher demand will, in theory, offer higher potential cost savings from innovation. Certain new technologies can improve welfare beyond the private surplus gains for firms in an industry through the reduction of negative externalities. These externality reductions, such as reduced pollution, are one motivation for policy targeting increased innovation. Clancy and Moschini (2017) model different policy regimes, green energy mandates and carbon taxes. They find that the possibility of innovation was necessary in order for policies mandating the use of biofuels to be welfare-improving.

Empirical studies suggest policy impacts depend on the nature of the intervention and the type of technology. Lee and Lee (2013) found that energy-related innovation increased in the periods between 1976 and 2003. Johnstone et al (2010) argue that broad policies, such as tradeable certificates, will increase innovation only in industries that are already “close to competitive” with fossil fuels, such as wind-generated power, whereas innovation associated with more costly energy sources such as solar require more targeted policies. Lindman and Söderholm (2016) found that feed-in tariffs and R&D support were complementary in improving innovation in wind power. An example of more targeted policies are solar “feed-in tariffs,” policies allowing consumers to sell solar energy back to the utility grid.

Prior R&D activity improves the quality of the status quo technology. Coupled with the increasing costs to R&D given in equation (2), this would mean that improvements over the status quo require rapidly increasing levels of R&D input expenditures. Policies supporting R&D may not be enough to make innovation profitable due to these increased costs. Nemet (2009) found that wind power innovation was not strongly impacted by California policies introduced after large innovation gains had occurred, leaving limited areas for improvement. Popp et al (2011) found similar results in the pulp sector, where demand for low-chlorine paper led to increased innovation prior to the introduction of regulation. Inclusion of ethanol improves gasoline’s octane rating and lowers carbon monoxide emissions, so the practice of ethanol blending predates mandates, evidence of a non-policy source of demand. The perception of biofuels as “green” could contribute to a demand for biofuel blends for consumers who have strong normative preferences for goods with low environmental impact. Findings from Albers et al (2016) suggest that there may be some exhaustion of R&D opportunities in traditional biofuels, as there is a trend of declining innovation in biofuels combined without a reorientation of R&D toward advanced biofuels.

Our study is aimed at investigating the impact of biofuels policies not only on innovation

within the biofuels sector but also on innovation in the related plant biotechnology sector. We investigate which, if any, policies will increase innovation in the biofuels sector, followed by an analysis of whether biofuels-oriented policies also impact innovation in plant biotechnology.

Policies are not homogeneous. While policies aimed at protecting domestic firms from foreign competition or incentivizing exports are demand-side measures that would in theory have similar impacts to mandates, they are tested separately. Protection from imports can also relax competition, which could give firms fewer incentives to cut costs and decrease the need to innovate. Tax incentives, R&D subsidies, and similar policies provide supply-side incentives.

## Data

We consider a country-year panel of 21 primarily OECD countries spanning 1996 to 2010. Most countries had data available for all 14 years. Slovakia had 13 years in the sample, while Greece and Belgium each had 11 years.

### Patent Data

Companies engaging in R&D apply for patents on the inventions resulting from their research in order to protect these inventions as their intellectual property. Therefore, information on patenting activity provides information on R&D activity and can provide insights into the relationship between R&D and other properties of the firm. We use patent data from OECD PATSTAT, the European Patent Office’s Worldwide Patent Statistical Database, to construct the dependent variables in our analysis. Each patent has an International Patent Classification (IPC) code assigned by patent examiners that indicate to which industry the patent is most relevant. The technologies of interest relate to biofuels technologies and plant science, with separate variables constructed for technologies listed exclusively in each category and those with multiple IPCs that have at least one IPC that corresponds to each category. The bibliometric literature on patents suggests that data on patents is a useful substitute for scarcer firm-level data on research expenditures and returns. Following OECD guidelines on which patent categories were relevant for biofuels, we consider patents listed in biofuels (patents in IPC categories C10, C02, C07, C11, C12, Y02) and plants (A01, A01) and separate those listed exclusively in each category from those listed in both, which we refer to as “bio-plant” (BP) patents (World Intellectual Property Organization 2017) . We give descriptions of these categories in table (1) at the four-digit level, though patents extracted were generally from more detailed sub-categories of these IPCs.

Table 1: Table of IPC Headings

IPC Category	Description	Label
C02F	Biological Treatment of Water, Wastewater, Sewage, or Sludge	Biofuels
C07C	Acyclic or Carbocyclic Compounds	Biofuels
C10B	Destructive Distillation of Carbonaceous Materials	Biofuels
C10G	Hydrocarbon Oils	Biofuels
C10L	Use of Additives to Fuels or Fires	Biofuels
C11C	Fats, Oils and Fatty Acids Obtained by Chemical Modification	Biofuels
C12M	Apparatus for Enzymology or Microbiology	Biofuels
C12N	Microorganisms or Enzymes	Biofuels
C12P	Fermentation/Enzyme-Using Synthesis of Desired Chemical Compound	Biofuels
Y02E	Reduction of GHG Related to Energy Generation/Distribution	Biofuels
A01G	Horticulture, Cultivation, Forestry, Watering	Plant
A01H	New Processes for Obtaining Plants	Plant

We use raw patent counts as the measurement of R&D effort. Previous studies on patents have used raw patent counts, the literature on patenting suggests that raw patent counts useful as a proxy measurement for R&D “input” or resources dedicated to research (Hausman et al 1984; Griliches et al 1987). We assigned a raw patent count by country-year. The address for inventors determined where to assign the patent. If more than one inventor was included for a patent, we divided the credit between the inventors’ countries of residence.

More recent patent bibliometrics literature focuses on the value of innovative output. Quality-weighted patents more closely correspond with the value added to firms than raw patent counts (Griliches 1990; Hall et al 2005; van Zeebroeck 2010). PATSTAT contains several measurements of the quality of patents. We use the broadest measurement of patent quality, quality index 6 score. Quality index 6 (QI6) considers six components of quality: forward citations, backward citations, patent family size, patent generality, grant lag, and number of claims (OECD 2012). A quality weighted patent total per country-year is constructed as  $y_j = \sum_i^n q_i$  where  $q_i$  is the quality score for each patent in IPCs associated with technology category  $j$  in that country-year. Table (2) shows the summary statistics for individual patents within a sample. In general, patents within these IPCs had lower quality index scores than the average patent, which had a QI6 score between .2 and .25 during the same time period (Squiccarini et al 2013).

Table 2: Summary Statistics for QI Scores of Individual Patents

Variable	Mean	Std. Dev.	Min	Max
Biofuel Patent Quality Index	0.114002	0.062959	0	0.344625
Plant Quality Index	0.069266	0.055596	0	0.243278
Bio-Plant Quality Index	0.092101	0.084454	0	0.380423

## Policies

Our analysis focuses on policies designed to stimulate the production and use of biofuels. Biofuels policy data are gathered from the fertilizer and biofuels support policies database which is maintained by the Trade and Agriculture Directorate of the Organization for Economic Co-operation and Development (OECD). The database covers the time period from 1995-2012 and is based on public sources and government information. We construct a country-year panel of countries that included all policy variables from 1996-2010, wherein we have coverage of the variables of interest. The novelty of these data are the measurement of support policies along the supply chain for biofuels. For the purposes of this research we are concerned with identification of the effect of biofuels mandates on intellectual property quantity and quality. Below each variable is described, along with the types of policies included if the variable is an aggregation of multiple policies. Table (3) describes the policy variables.

Table 3: Country-Year Descriptions of Policy Variables

Variable	Scale	Mean	Standard Dev
Ethanol Blend Mandate	percent volume	0.330266	1.021511
Biodiesel Blend Mandate	percent volume	0.090295	0.48103
Feedstock Producer Incentives	binary	0.029304	0.168967
Import Measures	binary	0.076923	0.266959
Intermediate Supplier Incentives	binary	0.051282	0.220978
Producer Investment Incentives	binary	0.175824	0.38137
Research and Development Support	2010 dollar PPP	3412.424	27377.69
Sustainability Criteria	binary	0.080586	0.272698
Tax Incentives	binary	0.362637	0.481644

To give a more accurate evaluation of the impact of blend mandates, we weight the mandate by the percentage in the country's overall fuel mix —diesel or gasoline — with which the type of biofuel is blended. Intuitively, this was done because the fuel mix determines the actual impact of the mandates. For instance, even a 100% ethanol blend mandate would have little impact in a country where vehicles primarily operate using diesel. To incorporate this we multiplied the ethanol blend mandate variable percentage of gasoline and the biodiesel blend mandate by the percentage of diesel in the fuel mix. If there was a generic biofuels blend mandate instead of a mandate targeting ethanol or biodiesel that was higher than either specific mandate, we replaced the specific mandate with the generic mandate. The information on the fuel mix was obtained using International Energy Agency data (IEA, 2016). Figures (2) and (3) show the prevalence of, respectively, ethanol and biodiesel blend mandates. The maximum weighted ethanol blend mandate was 9.1 per cent, while the maximum weighted biodiesel blend mandate was 3.78 per cent.

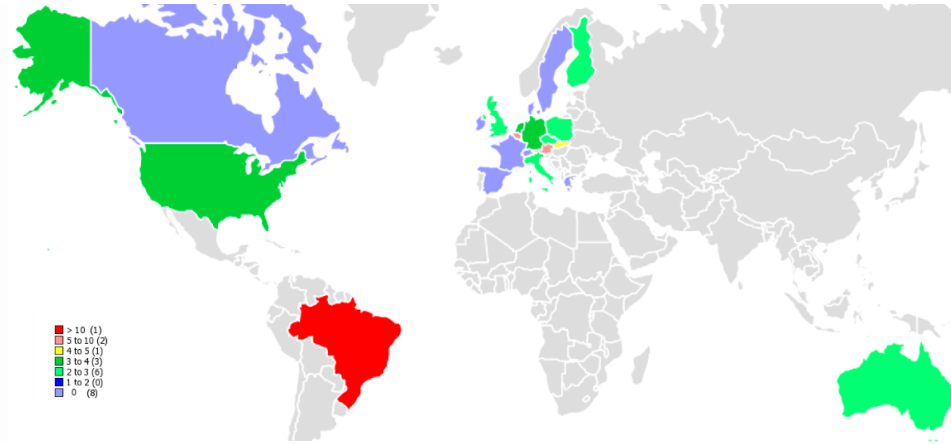


Figure 2: Ethanol Blend Mandates, Years with Mandate

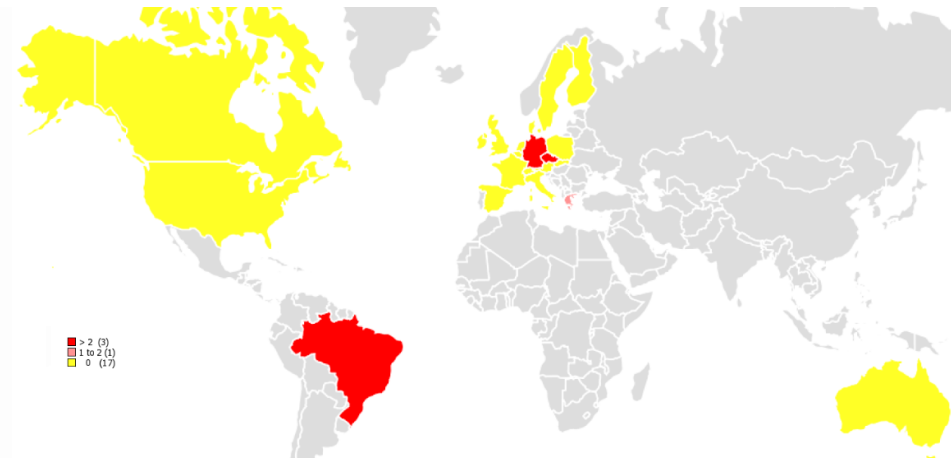


Figure 3: Biodiesel Blend Mandates, Years with Mandate

We included the level of R&D spending by governments to support biofuels research. This was expressed as total expenditures adjusted for purchasing power. This variable was the only policy variable that explicitly targeted R&D, though subsidies at other points in the supply chain such as investment incentives could affect R&D if investment is directed toward research activity.

For other policies, exact scale comparisons were difficult due to different implementation of the policies. An example of this is tax policies, ranging from reductions in corporate income tax rates to fuel excise tax exemptions. In the econometric analysis, we were only able to include such tax policies in a binary fashion — presence or absence in a given year — within certain categories. Policies creating incentives for the production of feedstock exclusively for biofuels use are classified as feedstock production incentives. Subsidies at any stage of the production supply chain are considered producer investment incentives, which include support to capital, land, and intermediate inputs. Intermediate supplier incentives (ISI) indicate the presence of subsidies directed toward storage, handling, transportation,

blending, or distribution of biofuels. ISI also includes credit concessions for throughput. A generic tax incentives variable was considered separately and indicates if a country has taxes directed toward production, intermediate supply, or consumption.

Certain countries had a sustainability criteria condition for biofuels production. This policy required a minimum life-cycle emissions savings for production of biofuels. It primarily was intended to limit the types of land that could be used for biofuels production, such as restrictions on deforestation. We included other environmental policies not directly related to biofuels production as control variables, which will be in the auxiliary variable set in our Bayesian model averaging approach.

Several other policies were considered for inclusion but later dropped due to low variation within our sample, either having no variation within the sample (e.g. a dummy variable with only 0 observations) or a single country-year observation different from the remainder of the observations. These include export measures such as value added tax refunds on exports, biofuels quantity targets related to overall volume rather than percentages, domestic price regulation of biofuels, output based biofuels payments, and purchase support for biodiesel and ethanol.

## Control Variables

We control for several factors that could impact innovation relevant to biofuels. These are related to market forces outside of policy, environmental policies unrelated to biofuels, and a measurement of prior accumulated knowledge capital within a country (“knowledge stock”). To control for the impact of market forces unrelated to policy, we include indices for crop production, food price, and energy price (FAO, 2017). Data necessary to construct an energy price index is not available for Brazil. Since Brazil is one of the largest users of biofuels, particularly bioethanol, we include specifications that do not have this variable in order to preserve Brazil in the sample.

Policies related to the stringency of environmental protection may also impact energy innovation. Porter (1991) introduced the concept, an application of the Hicks induced innovation hypothesis to policies aimed at forcing firms to internalize pollution abatement costs. Porter’s argument is that stricter environmental regulations will produce innovations in pollution abatement technologies or less polluting versions of products. Subsequent studies have supported limited versions of this argument (Jaffe and Palmer 1997; Lanoie et al 2011; Rubashkina et al 2015, Calel and Dechezleppêtre 2016). In deference to these findings, we include variables measuring the stringency of environmental policies in each country in the set of control variables. The five measurements of environmental stringency we include are sulfur dioxide emissions, petroleum excise taxes, environmental vehicle and transportation tax revenue, energy tax revenue, and the environmental policy stringency index.<sup>1</sup>

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<sup>1</sup>All aforementioned variables were gathered from OECD Stat with the exception of sulfur dioxide emissions and Brazilian petroleum excise tax. SO<sub>2</sub> emissions were gathered from the Community Emissions Data System (CEDS, 2018) and Brazilian petroleum excise tax was calculated by dividing total petroleum excise tax revenues by ktoe energy equivalent transportation fuel quantities, both of which were obtained from the International Energy Agency data (IEA, 2016).

We also control for the knowledge stock in a country. Knowledge stock is a discounted sum of prior patent activity in a country. Previous patenting demonstrates a country’s propensity for R&D. Popp (2002) demonstrates that omission of a country’s knowledge stock will significantly bias any analysis of patent data. The knowledge stock variables are constructed using the PATSTAT database. The knowledge stock variable is a discounted aggregate of previous years’ patent counts in all categories. We include IPC-specific knowledge stock limited to the constituent IPCs used in constructing the dependent variables. We use both citation-weighted and raw measurements of the IPC-specific knowledge stocks in different model averaging runs.

## Methodology

We begin with the standard fixed-effects OLS model for a country-year panel is given in equation (8). In addition to country fixed effects  $\xi_i$ , we also include a linear time trend. Because the trend in patenting dramatically dropped in the years following the 2008 recession, we include a dummy variable  $\gamma_{t>2008}$  to indicate post-2008 years, and include an interaction between the time trend and the post-2008 dummy to allow the time trend to differ in pre- and post- 2008 years.

$$y_{it} = \alpha + \beta X_{i,t-L} + \xi_i + \rho t + \gamma_t + \gamma_{t>2008} \phi t + \nu_{it} \quad (8)$$

Previous studies have shown little effect of foreign policies on innovation (Popp 2006) or that foreign policies have an impact far smaller than that of domestic policies (Dechezleppêtre and Glachant 2013). We therefore only include a country’s own policies and do not estimate the cross-country effects of policies.

The subset of  $X_{it}$  comprised of control variables is highly collinear, but there is uncertainty a priori as to which individual control variables to include and which to exclude. There is also uncertainty regarding the relevance of environmental regulations. A recent meta-analysis by Cohen and Tubb (2018) found conflicting evidence of the validity of the Porter Hypothesis that more stringent environmental regulations will produce greater pollution-reducing innovation. We also have evidence that the overall knowledge stock is a significant variable to include, but prior research does not provide guidance on how technology-specific accumulated knowledge will impact our focal technologies.

We include  $l \in [-2, -1, 0, 1, 2]$  as a lag from when the policy was implemented, with  $L = 0$  representing the contemporaneous period. Our analysis emphasizes the impacts in the contemporaneous period, as the literature suggests that patents are strategically timed to coincide with commercialization of the technology (Hopenhayn and Squintani 2015). However, we investigate specifications with lagged policies in order to investigate potential non-contemporaneous effects.

Instead of an ad-hoc approach to including or excluding variables in order to avoid collinearity, we use Bayesian Model Averaging (BMA), described below. This approach allows for

a statistically consistent way of testing the validity of various specifications. Independent variables are split into “focus” and “auxiliary” sets, with focus variables included in all candidate models and combinations of auxiliary variables included in candidate models. The approach allows us to test models including different combinations of the control variables while excluding others. This method is a Bayesian approach to the OLS model in which the probability of including a subset of the explanatory variables is uncertain (Mitchell and Beauchamp 1988; Raftery et al 1997; Hoeting et al 1999; Moral-Benito 2012).

The BMA process fits a series of candidate models conforming to (8) but including different subsets of controls in  $X_{it}$  to the data and computes the coefficients for the regressors by weighing the different estimates for each coefficient by the marginal likelihood of observing the dependent variable when using that model. Model averaging methods are useful in cases where there are a large number of potential explanatory variables and uncertainty over which regressors should be included. A common application of the BMA approach is in the cross-country growth literature (Brock and Durlauf 2001; Fernandez et al 2001; Eicher et al 2009). The use of fixed effect models within a BMA framework appears in growth and trade analyses (Léon-González and Montolio 2004; Tsangarides 2004; Mirestean and Tsangarides 2009; Chen et al 2009; Magnus et al 2010). The basic fixed-effects OLS model on which our BMA analysis is based is:

$$y_{it} = \alpha + \beta X_{i,t-L} + \delta Z_{it} + \xi_i + \rho t + \gamma_{t>2008} + \gamma_{t>2008} \phi t + \nu_{it} \quad (9)$$

$X_{i,t-L}$  is a vector of policy variables in country  $i$  in year  $t - L$ ,  $Z_{it}$  a vector of auxiliary regressors, country-level controls in country  $i$  in time  $t$ . The remaining terms are the same as those in equation 8. We apply BMA to this model where the  $X$  variables are the “focus” regressors and are always included while different models contain combinations of the “auxiliary”  $Z$  variables.<sup>2</sup> The basic constituent equations of the BMA process are given in Hoeting et al (2009). Computing the posterior probability distribution of a value of interest  $\Delta$  given the data uses the approach in equation (10).  $M_j$  is a candidate model from the set  $\mathcal{M}$  of  $K$  possible models  $\mathcal{M} = M_1, M_2, \dots, M_K$  equal to the number of subsets produced by combinations of auxiliary regressors, assuming that the probability of each model being the true model is positive and that all probabilities sum to one. The observed data is represented by  $D$ . The posterior probability of the model  $M_j$  is given by equation (11). Each BMA in our analysis had a model space of 16,384 candidate models when all control variables were included.

$$pr(\Delta|D) = \sum_{j=1}^K pr(\Delta|M_j, D)pr(M_j|D) \quad (10)$$

$$pr(M_j|D) = \frac{pr(D|M_j)pr(M_j)}{\sum_{l=1}^K pr(D|M_l)pr(M_l)} \quad (11)$$

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<sup>2</sup>Though not of interest for analysis, the fixed effects and time trends are in all models alongside the “focus” regressors.

The estimates for the  $\beta$  coefficients, the value of interest in this study, are generated through weighting the coefficients estimated by each candidate model. We repeat this process for patents exclusive to biofuels IPC codes, patents exclusive to plant IPC codes ("plant"), and patents listed in both biofuels and plant IPC codes ("BP"). Estimates for the parameter  $\beta$  are given by equations (12) and (13).

$$E(\beta|D) = \sum_{j=1}^K E(\beta|D, M_j)pr(M_j|D) \quad (12)$$

$$var(\beta|D) = \sum_{j=1}^K pr(M_j|D)var(\beta|D, M_j) + \sum_{j=1}^K pr(M_j|D)[E(\beta|D, M_j) - E(\beta|D)]^2 \quad (13)$$

This process models the condition expectation and variance of the parameter given the data  $D$  as a sum of the estimates from each model  $M_j$  weighted by the probability of model  $M_j$  being the true model given the data. The process generates a posterior distribution of the parameter estimates with Bayesian confidence intervals based on the computed mean and variance estimates. We use a 90% posterior confidence interval to determine if the parameter estimate for a regressor in the focus set is significant.

For auxiliary variables, we determine significance using the estimated posterior inclusion probability (PIP). Posterior inclusion probability represents the number of models in which an auxiliary variable appeared weighted by the posterior probability of those models being the true model. A coefficient with a PIP of 0.5 or higher is considered significant (Magnus et al 2010, De Luca and Magnus 2011). PIP is uninformative for focus regressors, which always have a PIP of 1.0.

We first consider the basic question of whether the policies impact quality-weighted innovation in biofuels patent categories. Next, we estimate the impact of these policies on plant-related patents and patents classified as both biofuels and plant biotechnology (BP). We use the same approach to measurements of raw patent counts to determine the level of effort firms exert toward R&D. We repeated the process for time periods one and two years before the policies went into effect and one and two years after the policies went into effect to see if firm behavior changed in the years following passage of the policies. We ran 30 BMAs total, six for each different policy time lag.

## Results and Discussion

Biofuels policies do not have a monolithic effect on biofuels patenting or plant patenting. Certain policies are effective in increasing biofuels innovation, while others have negative or insignificant effects on biofuels patenting. Other policies have cross-category negative effects within time periods and across time periods. The presence of spillovers also causes changes in effort in one category to impact other categories. Since there is a random component

to R&D output, it is possible that increased R&D inputs may not have a positive effect on innovative output, and this is reflected in some findings. Since theoretical predictions suggest that firms will delay patenting until close to commercialization (Hopenhayn and Squintani 2015), our analysis focuses on the contemporaneous effects of policies rather than lagged versions.

Tables (4) and (5) show the results from the BMA process for the policy variables. Coefficient estimates are averages of the estimates from each candidate model, weighted by the posterior probability of that model being the true model. The values in parentheses are 90% Bayesian posterior probability intervals. The output is from the specifications without the energy price index included and therefore contains our entire 21-country sample.

Table 4: Model Averages, Raw Patent Counts

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	18.24 (4.321, 32.16)	-4.243 (-7.820, -0.666)	-3.820 (-10.11, 2.469)
Biodiesel Blend Mandate	-6.370 (-24.52, 11.78)	-5.155 (-9.653, -0.658)	1.938 (-6.488, 10.36)
Feedstock Prod. Incent.	-48.21 (-96.69, 0.263)	-11.83 (-24.43, 0.770)	-8.496 (-32.04, 15.04)
Import Measures	-96.53 (-209.0, 15.91)	5.535 (-24.93, 36.00)	-18.52 (-70.90, 33.86)
Intermediate Sup. Incent.	-20.73 (-62.29, 20.83)	-3.218 (-13.61, 7.171)	13.29 (-6.068, 32.64)
Producer Inv. Incent.	45.80 (13.17, 78.43)	5.124 (-3.175, 13.42)	4.175 (-11.14, 19.49)
R&D Support	1.65e-05 (-3.46e-04, 3.79e-0)	-9.19e-05 (-1.74e-0, -9.84e-06)	6.79e-05 (-9.62e-05, 2.32e-04)
Sustainability Criteria	-6.623 (-53.89, 40.65)	-8.488 (-20.46, 3.479)	8.489 (-13.91, 30.89)
Tax Incentives	-28.58 (-51.98, -5.176)	-0.775 (-6.777, 5.226)	-17.36 (-28.50, -6.209)
Observations	287	287	287
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 5: Model Averages: Quality-Weighted Patenting

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	4.752 (2.312, 7.193)	-0.00502 (-0.602, 0.592)	0.487 (-0.239, 1.213)
Biodiesel Blend Mandate	0.938 (-2.273, 4.150)	-1.264 (-2.032, -0.496)	0.622 (-0.289, 1.533)
Feedstock Prod. Incent.	-6.541 (-15.03, 1.943)	-0.833 (-3.003, 1.338)	-0.197 (-2.783, 2.390)
Import Measures	-26.15 (-46.85, -5.456)	-5.454 (-10.40, -0.511)	-7.855 (-14.24, -1.475)
Intermediate Sup. Incent.	-3.060 (-10.41, 4.292)	-0.208 (-2.006, 1.589)	0.443 (-1.684, 2.571)
Producer Inv. Incent.	4.291 (-1.622, 10.20)	1.540 (0.139, 2.941)	-0.0995 (-1.799, 1.600)
R&D Support	-4.93e-05 (-0.000115, 1.66e-05)	-1.83e-05 (-3.25e-05, -4.06e-06)	1.90e-05 (2.23e-06, 3.57e-05)
Sustainability Criteria	1.745 (-6.876, 10.37)	-1.417 (-3.470, 0.635)	1.281 (-1.203, 3.765)
Tax Incentives	-6.440 (-10.61, -2.273)	-1.114 (-2.142, -0.0862)	-2.470 (-3.687, -1.252)
Observations	287	287	287
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

## Blend Mandates

Blend mandates for ethanol and biodiesel have different effects. Ethanol blend mandates significantly increase raw and quality weighted biofuels patents. Non-commercial patenting follows the same pattern, though there is also an increase in biofuels raw patent counts for non-commercial patenting. Based on raw patent counts, efforts toward biofuels research increase while efforts toward BP decrease in response to ethanol blend mandates.

There is evidence of a substitution effect in R&D effort expended toward the different categories resulting from ethanol blend mandates. Within time periods, significant coefficients for raw patent counts have opposite signs for biofuels and the other categories. When ethanol blend mandates have a significant, positive relationship to raw patent counts, their impact on BP and plant patents was significant and negative or insignificant. In the contemporaneous specification, the effect of ethanol blend mandates on biofuels RPC is positive while the coefficients for Bio-plant RPC is negative. When considering only OECD countries, meaning excluding Brazil, the impact of ethanol blend mandates on plant-exclusive RPCs was also negative but these policies continued to have no significant effect on the quality-weighted patent output. However, this finding was not robust to other specifications of the knowledge stock, namely the use of raw patent counts for individual IPCs' knowledge stocks instead of citation-weighted variants. While the significant negative coefficient remained for the plant raw patent count, the impact on biofuels raw patent count was no longer significant.

The coefficients for the ethanol blend mandate's impact on different quality-weighted patent counts do in some specifications have the same sign. In the one-year lag specification, both are negatively impacted. This provides some support for the hypothesis of a relationship between innovation in the two categories. Since the policies would not affect the parameter governing scientist labor productivity, we believe that an increase in quality-weighted patenting or null coefficient in the presence of decreased raw patent counts for that IPC category is evidence for spillovers, as the level of total technology is increasing or remains the same even as  $x_i$  decreases. Since total cost-saving innovation in a field is given by  $x_i + s_{ij}x_j$  and is a function of research labor in other technology categories, our theoretical spillover model's predictions would be supported by the finding.

There is potential evidence that the spillover effect exists in the responses to ethanol blend mandates. However, our model of innovation production suggests that if one technology were to increase, it could be optimal to reduce efforts toward development in another category. If the policies result in higher levels of  $Y_{biofuels}$  and therefore an increase in the optimal level of  $x_{biofuels}$ , then the spillovers could result in the previous level of  $x_{plant}$  and  $x_{bio-plant}$  being above the optimal level, with the firms reducing R&D inputs toward the fields in order to obtain the optimum.

Biodiesel blend mandates did not significantly impact the weighted patent count for commercial biofuel or plant patenting but had a negative impact on raw and quality-weighted bio-plant patenting. Biodiesel blend mandates increase non-commercial raw patent counts and quality-weighted patent output of biofuels but do not significantly impact commercial patenting. It is possible that due to patenting occurring outside the private sector, the pri-

vate innovation was “crowded out” or discouraged, as useful technologies were the intellectual property of the academic or public sector, which produces more R&D toward the “advanced” biofuels feedstocks than the private sector (Albers 2016).

Biodiesel blend mandates had inconsistent and typically insignificant effects. This could be attributed to the comparably low number of observations in which any biodiesel blend mandates were present; only 15 of the 287 contemporaneous observations had any type of mandate for biodiesel. Likely due to this, there were high estimated variances for the coefficients. These policies reduced or did not significantly impact raw patent counts for biofuels depending on the time period. Since raw patent counts for biofuels, as well as the other categories, were not impacted by the biodiesel mandates in those time periods, we do not take this as evidence that the policy drove the increase in innovation.

## Other Policies

Import measures did not have a significant effect on raw patent counts. However, in the contemporaneous period these policies reduced the quality-weighted patents in plant categories. In the specification with a two-year lag, quality-weighted patents increased in all three categories.

Intermediate supplier incentives increased raw plant patenting and decreased weighted biofuels patenting. This finding, however, was not consistent when applying leads or lags to the policies.

Producer investment incentives increased raw patenting in biofuels IPC categories while increasing quality-weighted counts in biofuels. These policies decrease the cost of investment, including investment in R&D. Since this can be seen as decreasing R&D input price  $w$  or raising the R&D budget  $\bar{x}$  in equation (2) it would increase the optimal level of  $x_i$  and  $x_j$  used for research based on the comparative statics demonstrated in equations (6) and (7). The findings in the contemporaneous period support this prediction. The two-year lagged version showed an increase in plant raw patent count and quality-weighted patent counts. A one-year lag of producer investment incentives produced a significant increase in biofuels raw patent counts without an increase in quality-weighted patent counts. However, even though there was no significant increase in raw patent counts in plant patenting or BP patenting, each had increases in quality-weighted patents in response to producer investment incentives. With a one-year lead or two-year lead, there were no significant coefficients for these policies. It is possible that firms adjusted their timing in order to take advantage of the policies, but once policies were in effect, they consistently increased efforts in at least one category while not decreasing effort anywhere else.

While R&D support, a measurement of government spending on research, should have a similar effect, it did not increase R&D spending by private firms as proxied by raw patent counts. Quality-weighted counts for biofuels and BP decreased. Quality-weighted plant patenting did increase significantly, despite R&D support not resulting in increased plant inputs. It is possible that government and university R&D, while not reflected in the research effort of private firms or their output of biofuels and BP research, is increasing R&D output

for private firms in the plant sector via spillover, in turn crowding out private firms' research by raising the status quo technological level.

Tax incentives had a significant, negative effect for all dependent variables in the contemporaneous period. In other specifications, there were either significantly negative coefficients or no significant effect.

## **Controls: Environmental Policies, Agricultural and Energy Prices, and Knowledge Stock**

We assigned control variables to the auxiliary regressor set in the BMA process. Therefore, we interpret as significant those variables with posterior inclusion probabilities greater than .5, as these regressors were included in the true model with greater than 50 per cent likelihood. The coefficients are computed in the same manner as the "focus" regressors. Tables 6 and 7 show the results for the control variables. For these tables, the estimates are from the specification with all control variables, so only 20 countries were included in the sample. Brazil was excluded due to the absence energy price index data. When Brazil was included but the energy price index variable was omitted, there were not major differences.

Our measurement for environmental vehicle and transportation tax revenue had a significant, negative effect on biofuels raw patent counts and quality-weighted biofuels patent counts. The same variable had a significant, positive effect on BP patent counts. Other environmental variables did not significantly impact raw patenting in any of the IPCs considered.

These findings do not strongly support the Porter hypothesis that environmental regulation can promote R&D and leave an industry more efficient. Instead, the findings are limited, with vehicle taxes contributing negatively to biofuels research effort. The energy policy stringency index, a more comprehensive measurement of regulations, had a negative effect on R&D output but did not affect R&D inputs in any categories.

Energy prices, measured by the energy price index variable, had a significant, positive effect on raw patent counts for plant IPCs. None of the other indices related to prices or production levels were significant.

Though the small set of countries in the sample prevented creating trade dyads to investigate international impacts, we did include a global average of ethanol blend mandates for each year. Including this variable did not impact the sign or significance of the coefficients in the focus set, but in the auxiliary set, it did have a PIP greater than .5 for quality-weighted biofuels patenting, biofuels raw patent count, and bio-plant raw patent count.

The findings related to knowledge stock supported the Popp (2002) finding that omitting knowledge stock will bias the results. The knowledge stock for all categories was included in the focal regressor set, but when treated as an auxiliary variable, its PIP was 1 or near 1 in all specifications, confirming Popp's findings. The knowledge stocks for individual patent categories were also significant in most specifications. While difficult to consider evidence of spillovers, as there were both positive and negative cross-category effects, it does support

that there are connections between R&D in the different technology categories.

Table 6: Auxiliary BMA Variables, Raw Patent Counts

VARIABLES	Biofuels		Biofuels-Plant		Plant	
	Post. Mean	PIP	Post. Mean	PIP	Post. Mean	PIP
Sulfur Dioxide Emissions	0.000858	0.07	0.000217	0.07	0.001356	0.1
Env. Poli. Stringency	-8.55981	0.31	-0.11439	0.06	-5.23224	0.36
Petroleum Excise Tax	0.061413	0.1	-0.01891	0.1	-0.06143	0.14
Env Transp Tax Rev	-0.02509	0.98	0.002552	0.54	0.000922	0.18
Energy Tax Rev	0.001274	0.34	4.63E-05	0.09	1.53E-05	0.06
Food Price	-0.22638	0.11	0.059404	0.11	-0.2119	0.17
Agricultural Output	0.001341	0.06	0.006077	0.07	0.056568	0.14
Energy Price	-0.02818	0.06	0.04465	0.13	0.821917	0.66
Knowledge Stock A01	-1.02E-06	0.19	6.60E-06	1	-6.41E-06	0.98
Knowledge Stock C02	0.000342	0.98	-9.6E-05	0.97	-4.71E-06	0.18
Knowledge Stock C07	-1.4E-05	0.99	3.86E-06	0.98	-1.70E-07	0.22
Knowledge Stock C10	-0.00055	1	-3.1E-05	0.57	-8.6E-05	0.96
Knowledge Stock C11	0.000197	1	1.76E-05	0.61	2.06E-07	0.12
Knowledge Stock C12	-4.62E-07	0.13	-5.29E-06	1	2.88E-06	0.97

Posterior means (Post. Mean) are reported along with posterior inclusion probabilities (PIP) for each variable.

Table 7: Auxiliary BMA Variables, Quality-Weighted Patents

VARIABLES	Biofuels		Biofuels-Plant		Plant	
	Post. Mean	PIP	Post. Mean	PIP	Post. Mean	PIP
Sulfur Dioxide Emissions	-0.00032	0.08	-2.2E-05	0.06	-2.6E-05	0.08
Env. Poli. Stringency	-1.62458	0.33	-0.04876	0.08	0.020229	0.06
Petroleum Excise Tax	0.01716	0.12	0.000879	0.07	0.004363	0.11
Env Transp Tax Rev	-0.00568	1	0.000108	0.2	7.38E-06	0.07
Energy Tax Rev	0.000111	0.2	3.84E-05	0.25	2.94E-06	0.06
Food Price	0.007819	0.06	0.003407	0.07	0.002807	0.06
Agricultural Output	-0.00379	0.07	0.003439	0.11	0.00291	0.09
Energy Price	-0.06124	0.21	-0.00266	0.08	-0.00041	0.06
Knowledge Stock A01	-9.21E-07	0.44	1.15E-06	1	-1.01E-06	0.97
Knowledge Stock C02	6.14E-05	1	-2.2E-05	1	2.61E-06	0.46
Knowledge Stock C07	-2.21E-07	0.19	7.98E-07	1	1.27E-07	0.53
Knowledge Stock C10	-8E-05	1	2.02E-07	0.08	-9.01E-06	0.79
Knowledge Stock C11	-1.6E-05	0.91	7.72E-06	1	-7.00E-06	0.95
Knowledge Stock C12	-2.07E-06	0.92	-9.57E-07	1	3.63E-07	0.8

Posterior means (Post. Mean) are reported along with posterior inclusion probabilities (PIP) for each variable.

## Conclusion

This study demonstrates that biofuels policies impact private sector R&D in biofuels and agricultural biotechnology. Ethanol blend mandates were clearly associated with increased R&D effort in biofuels and higher total production of quality-weighted patent output. Biodiesel blend mandates and others produced less noticeable effects in regard to this benefit. Previous literature has empirically demonstrated effects on food prices and emissions, while theoretical analysis suggests that only in the presence of innovation would biofuels mandates be welfare-improving over status quo approaches (Clancy and Moschini 2017) .

While the impact of energy policy on innovation in other forms of alternative energies has been rigorously studied, biofuels were not included in these studies. We found that, similar to previously studied policies, certain biofuels blend mandates correlated with increased innovation. We extend our analysis of policy impacts by examining if policies impacting biofuels R&D have effects on innovation in other fields. Evidence of spillover effects is present, but only certain policies cause firms to incorporate these benefits into their investment strategies. The countervailing impact is substitution of aggregate R&D effort away from plant biotechnology. There is evidence that this effect negates the innovation gains in plant biotechnology that could be realized from the spillover effect. While biofuels policies can increase demand for biofuels, incentives for producing greater amounts of plant biotechnology remain unchanged or could even be reduced by land use changes favoring biofuels. Therefore, due to the technological spillovers from biofuels research, firms reduce their investment in bio-plant R&D, remaining at the same technological level and, therefore, the same level of output.

Ethanol blend mandates were more effective at promoting biofuels innovation than biodiesel blend mandates. However, the impact of this innovation appears limited by firms' decisions to substitute between R&D effort to biofuels research and that directed at bio-plant research rather than to increase or decrease both at once. Once the policies have been in effect for two years, the effect on R&D resource allocation is reversed. It is also possible that firms may face constraints, such as a limited supply of specialized scientists or facilities, that necessitate this tradeoff between research effort in one category and effort in another. When policies affect the demand for biofuels, the scarce scientific resources should in theory be reallocated toward that industry. Spillovers, in conjunction with the decreasing marginal returns to R&D investment can also explain why firms would decrease inputs to some technologies in response to policies while simultaneously increasing effort toward developing other technologies. Our results strongly suggest that biofuels policies have an impact on the R&D decisions of multiproduct firms in the agricultural sector.

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## Appendix: Lag and Lead BMA Specifications

Table 8: One-Year Lag, Raw Patent Counts

VARIABLES	Biofuels RPC	Bio-Plant RPC	Plant RPC
Ethanol Blend Mandates	10.52 (-9.869 - 30.91)	-2.325 (-7.401 - 2.751)	7.166 (-0.803 - 15.13)
Biodiesel Blend Mandates	-16.87 (-41.14 - 7.396)	-3.805 (-9.807 - 2.198)	-3.218 (-14.33 - 7.890)
Feedstock Prod. Incent.	-35.58 (-91.40 - 20.25)	-7.783 (-22.05 - 6.483)	-15.24 (-41.45 - 10.96)
Import Measures	-14.89 (-103.8 - 74.00)	-14.92 (-38.46 - 8.606)	-20.87 (-62.89 - 21.15)
Intermediate Sup. Incent.	-11.35 (-55.14 - 32.43)	-10.96# (-21.66 - -0.249)	-4.602 (-24.35 - 15.14)
Producer Inv. Incent.	40.20# (2.869 - 77.52)	7.718 (-1.439 - 16.87)	15.58 (-1.386 - 32.54)
R&D Support	6.41e-05 (-0.000284 - 0.000412)	-6.21e-05 (-0.000144 - 1.99e-05)	3.55e-05 (-0.000126 - 0.000196)
Sustainability Criteria	13.83 (-59.46 - 87.12)	-6.167 (-24.23 - 11.89)	31.70 (-1.815 - 65.21)
Tax Incentives	-36.24# (-64.83 - -7.649)	-0.423 (-7.636 - 6.790)	-14.60# (-27.62 - -1.592)
Observations	287	287	287
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 9: One-Year Lag, Quality-Weighted Patenting

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	-4.047 (-7.476 - -0.618)	-0.697 (-1.492 - 0.0985)	-1.103# (-2.017 - -0.189)
Biodiesel Blend Mandates	0.876 (-3.463 - 5.214)	-1.642# (-2.650 - -0.634)	-0.723 (-1.964 - 0.518)
Feedstock Prod. Incent.	-1.372 (-11.37 - 8.629)	0.0737 (-2.354 - 2.501)	-1.231 (-4.158 - 1.696)
Import Measures	9.040 (-6.923 - 25.00)	1.063 (-2.748 - 4.874)	6.090 (1.480 - 10.70)
Intermediate Sup. Incent.	-1.164 (-9.046 - 6.718)	-1.298 (-3.117 - 0.521)	-1.379 (-3.618 - 0.860)
Producer Inv. Incent.	6.301 (-0.450 - 13.05)	2.415# (0.866 - 3.965)	2.296# (0.379 - 4.212)
R&D Support	-3.49e-05 (-9.99e-05 - 3.01e-05)	-1.62e-05# (-3.01e-05 - -2.33e-06)	2.79e-06 (-1.40e-05 - 1.95e-05)
Sustainability Criteria	-2.556 (-15.74 - 10.62)	-3.192# (-6.249 - -0.135)	-0.981 (-4.686 - 2.724)
Tax Incentives	-6.816# (-12.14 - -1.488)	-1.467 (-2.669 - -0.266)	-2.651# (-4.088 - -1.215)
Observations	287	287	287
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 10: Two-Year Lag, Raw Patent Counts

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	-15.11 (-35.92 - 5.704)	1.450 (-3.812 - 6.712)	7.030 (-2.712 - 16.77)
Biodiesel Blend Mandates	-29.01 (-64.57 - 6.545)	-5.440 (-14.16 - 3.276)	-10.87 (-27.31 - 5.572)
Feedstock Prod. Incent.	-5.630 (-72.55 - 61.29)	-0.986 (-17.57 - 15.60)	-14.23 (-45.26 - 16.80)
Import Measures	26.18 (-62.19 - 114.5)	20.18 (-1.577 - 41.94)	20.80 (-20.01 - 61.61)
Intermediate Sup. Incent.	-19.53 (-67.54 - 28.49)	2.885 (-8.950 - 14.72)	-4.603 (-26.78 - 17.57)
Producer Inv. Incent.	32.16 (-5.828 - 70.16)	0.645 (-8.692 - 9.982)	18.94# (1.398 - 36.48)
R&D Support	1.05e-05 (-0.000325 - 0.000346)	-5.41e-05 (-0.000134 - 2.59e-05)	5.19e-05 (-0.000103 - 0.000207)
Sustainability Criteria	13.64 (-83.06 - 110.3)	2.160 (-21.43 - 25.75)	30.92 (-13.70 - 75.54)
Tax Incentives	-26.61 (-58.60 - 5.392)	-5.439 (-13.36 - 2.483)	-20.14# (-35.05 - -5.225)
Observations	268	268	268
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 11: Two-Year Lag, Quality-Weight Patenting

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	-5.856# (-9.567 - -2.146)	-0.742 (-1.727 - 0.243)	-1.022 (-2.128 - 0.0849)
Biodiesel Blend Mandates	-0.792 (-6.757 - 5.174)	-2.153# (-3.650 - -0.657)	-2.817# (-4.722 - -0.912)
Feedstock Prod. Incent.	7.070 (-4.272 - 18.41)	1.564 (-1.336 - 4.465)	-0.487 (-4.080 - 3.107)
Import Measures	21.90 (6.913 - 36.89)	5.466 (1.768 - 9.164)	5.206 (0.532 - 9.879)
Intermediate Sup. Incent.	-5.525 (-13.66 - 2.609)	-0.454 (-2.498 - 1.591)	-1.948 (-4.562 - 0.666)
Producer Inv. Incent.	3.742 (-2.653 - 10.14)	0.809 (-0.792 - 2.411)	3.127# (1.093 - 5.161)
R&D Support	-1.60e-05 (-7.20e-05 - 4.00e-05)	-6.96e-06 (-2.07e-05 - 6.83e-06)	-6.79e-06 (-2.41e-05 - 1.05e-05)
Sustainability Criteria	0.596 (-15.63 - 16.82)	-2.670 (-6.767 - 1.427)	-0.430 (-5.599 - 4.740)
Tax Incentives	-1.332 (-6.872 - 4.209)	-0.625 (-1.994 - 0.745)	-0.749 (-2.474 - 0.977)
Observations	268	268	268
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 12: One-Year Lead: Raw Patent Counts

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	0.301 (-12.79 - 13.39)	0.294 (-3.215 - 3.802)	7.355# (1.247 - 13.46)
Biodiesel Blend Mandates	0.697 (-16.72 - 18.11)	-6.693# (-11.06 - -2.322)	1.542 (-6.162 - 9.245)
Feedstock Prod. Incent.	-26.34 (-72.37 - 19.69)	-13.31# (-25.43 - -1.188)	-4.213 (-26.53 - 18.10)
Import Measures	107.2 (-7.320 - 221.7)	1.622 (-28.27 - 31.51)	5.969 (-47.61 - 59.55)
Intermediate Sup. Incent.	22.19 (-16.03 - 60.42)	-4.179 (-14.18 - 5.820)	16.31 (-1.913 - 34.53)
Producer Inv. Incent.	9.777 (-21.39 - 40.95)	-0.446 (-8.645 - 7.753)	-3.604 (-18.37 - 11.16)
R\&D Support	3.16e-05 (-0.000288 - 0.000351)	-6.27e-05 (-0.000143 - 1.72e-05)	4.94e-05 (-9.49e-05 - 0.000194)
Sustainability Criteria	-11.11 (-67.12 - 44.90)	-4.532 (-18.79 - 9.723)	11.42 (-13.83 - 36.66)
Tax Incentives	-37.03# (-58.92 - -15.15)	-1.254 (-7.033 - 4.525)	-16.92# (-27.48 - -6.362)
Observations	266	266	266
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 13: One-Year Lead: Quality-Weighted Patenting

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	1.205 (-0.705 - 3.115)	0.114 (-0.528 - 0.756)	1.369# (0.652 - 2.086)
Biodiesel Blend Mandates	1.975 (-0.518 - 4.469)	-1.087 (-1.911 - -0.264)	0.198 (-0.711 - 1.107)
Feedstock Prod. Incent.	-5.211 (-12.00 - 1.581)	-1.069 (-3.349 - 1.212)	-0.690 (-3.292 - 1.911)
Import Measures	18.92# (2.146 - 35.70)	2.391 (-3.217 - 7.999)	-0.491 (-6.766 - 5.785)
Intermediate Sup. Incent.	3.147 (-2.520 - 8.814)	-0.226 (-2.106 - 1.654)	1.607 (-0.531 - 3.744)
Producer Inv. Incent.	0.0974 (-4.468 - 4.663)	0.257 (-1.291 - 1.806)	-0.743 (-2.486 - 1.000)
R\&D Support	-3.45e-05 (-8.06e-05 - 1.16e-05)	-9.52e-06 (-2.43e-05 - 5.24e-06)	1.59e-05 (-9.74e-07 - 3.27e-05)
Sustainability Criteria	1.122 (-6.952 - 9.195)	-1.460 (-4.040 - 1.119)	0.849 (-2.061 - 3.760)
Tax Incentives	-7.623# (-10.86 - -4.391)	-1.122# (-2.208 - -0.0368)	-2.355# (-3.592 - -1.118)
Observations	266	266	266
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 14: Two-Year Lead, Raw Patent Counts

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	-22.33# (-35.40 - -9.250)	-2.089 (-5.556 - 1.378)	-2.329 (-8.942 - 4.284)
Biodiesel Blend Mandates	-14.37 (-30.87 - 2.123)	-3.893 (-8.244 - 0.459)	1.640 (-6.160 - 9.441)
Feedstock Prod. Incent.	-12.82 (-63.14 - 37.49)	-9.254 (-21.65 - 3.145)	-16.29 (-39.31 - 6.726)
Import Measures	-106.8 (-216.1 - 2.384)	5.040 (-23.91 - 33.99)	5.429 (-49.90 - 60.75)
Intermediate Sup. Incent.	32.63 (-5.939 - 71.20)	-0.276 (-10.45 - 9.895)	26.74 (7.964 - 45.52)
Producer Inv. Incent.	23.62 (-8.826 - 56.06)	4.934 (-3.687 - 13.56)	-4.190 (-20.41 - 12.03)
R\&D Support	-1.91e-05 (-0.000331 - 0.000292)	-3.77e-05 (-0.000118 - 4.29e-05)	-8.99e-06 (-0.000158 - 0.000140)
Sustainability Criteria	-70.68# (-127.8 - -13.51)	-3.931 (-17.66 - 9.803)	-1.711 (-27.39 - 23.96)
Tax Incentives	-39.14# (-62.44 - -15.83)	-0.346 (-6.320 - 5.629)	-5.670 (-16.62 - 5.280)
Observations	245	245	245
Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()			

Table 15: Two-Year Lead, Quality-Weighted Patenting

VARIABLES	Biofuels	Bio-Plant	Plant
Ethanol Blend Mandates	-1.213 (-3.221 - 0.795)	0.00975 (-0.660 - 0.680)	-0.380 (-1.082 - 0.321)
Biodiesel Blend Mandates	0.312 (-2.180 - 2.804)	-0.558 (-1.418 - 0.302)	0.562 (-0.300 - 1.424)
Feedstock Prod. Incent.	-3.213 (-11.01 - 4.579)	-1.050 (-3.483 - 1.383)	-2.050 (-4.546 - 0.446)
Import Measures	-12.09 (-29.36 - 5.182)	1.837 (-4.781 - 8.455)	5.583 (-0.393 - 11.56)
Intermediate Sup. Incent.	1.033 (-4.791 - 6.857)	-0.444 (-2.429 - 1.541)	1.703 (-0.348 - 3.754)
Producer Inv. Incent.	2.519 (-2.401 - 7.439)	0.809 (-0.869 - 2.487)	-0.194 (-1.981 - 1.592)
R\&D Support	1.24e-05 (-3.38e-05 - 5.86e-05)	-2.13e-07 (-1.58e-05 - 1.54e-05)	1.18e-05 (-4.39e-06 - 2.80e-05)
Sustainability Criteria	-1.430 (-9.579 - 6.720)	-1.129 (-3.757 - 1.498)	0.478 (-2.263 - 3.219)
Tax Incentives	-3.710# (-7.149 - -0.272)	-0.124 (-1.289 - 1.041)	-0.865 (-2.050 - 0.320)
Observations	245	245	245

Posterior means are displayed for each variable with 90% posterior confidence intervals shown in ()