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Demand-driven Technical Change and Productivity Growth: Theory and Evidence from the US Energy Policy Act

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Abstract

We study how demand shocks affect productivity by provoking technical change. Our model shows that increasing demand leads to technical change and productivity improvements through a direct market size effect and an indirect competition effect. We test the predictions using a natural experiment in the US corn industry where changes to national energy policy created exogenous increases in demand. Estimates show that the increase in demand caused technical change as corn producers adopted new technologies which in turn raised productivity by 5.7% per annum in the five years after the policy change. Although both channels are found to motivate technical change, the economic magnitude of the direct effect substantially outweighs the indirect effect.

JEL-Codes: D22, D24, L16, Q11.

Keywords: demand, market size, technical change, productivity.

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1 Introduction

New technologies are a key engine of productivity growth. While changes in firms' technology mix are often based on cost considerations, economists have recognized since at least Schmookler (1954) that the incentive to adopt productivity-enhancing technologies also depends on demand conditions. The size of the market is essential in shaping the incentives to introduce or adopt new technologies. In this paper we construct a simple model linking market size to technical change and productivity growth and provide evidence of a relationship between market size, technological progress and productivity in the corn industry. We use the theory to guide the empirical investigation of a natural experiment in the United States. The Energy Policy Act of 2005 (EPA) mandated an increase in the ethanol content of gasoline, thereby raising the market size for corn, the key intermediate input in the production of ethanol. Our empirical analysis finds that the demand shock experienced by the corn industry has strong and robust effects on technical change and productivity.

In our model, firms operate in oligopolistic industries and invest in new technologies to improve their productivity. Larger market size stimulates technical change because the benefits of productivity improvements are proportional to the quantity produced. Market size has a second, indirect, effect on technical change and productivity operating through firm entry. When an industry experiences an increase in demand, more firms enter thereby increasing product market competition. In this more competitive environment, firms are larger and therefore invest more in new technology. Hence, an increase in demand accelerates technical change and increases productivity through a direct *market size effect* and through an indirect *competition effect*.

We test these different channels in our empirical investigation of the effects of the EPA on productivity growth in the corn industry. The EPA sparked a wave of ethanol plant openings and triggered a sharp increase in market size for corn. Using county-level data we find that corn production rose by 37% against an increase in planted acreage of 8%, indicating that rising productivity was crucial in satisfying the higher demand for corn. The evidence indicates the change in productivity is driven by technical change: corn producers adopted a new seed technology. Following implementation of the EPA, the equilibrium number of corn firms in the average county increased by around 18% which also spurred technical change by increasing product market competition.

Key to valid identification is the exogeneity of the EPA with respect to technical change and productivity within the corn industry. As we outline below, the key driving force behind the legislation were fears among national policymakers that the US economy was vulnerable to interruption of overseas energy supplies. The EPA sought to improve energy independence and security through an array of measures including increased use of ethanol in gasoline to displace oil imports (Diggs, 2012). Neither productivity nor technological considerations within the corn industry motivated enactment of the EPA and there is no evidence of lobbying activity in the run up to the EPA by either corn or seed producers. Moreover, the legislation was introduced in the House of Representatives by a congressman from outside the Midwest, the area from which our sample is drawn. The plausible exogeneity of the demand shock is also reflected in a series of tests that examine the determinants of ethanol plant location. The location of ethanol plants were chosen strategically to minimize corn procurement costs (they located away from existing ethanol plants to avoid competition) and maximize revenue.[1] We are able to show in our data that their location was orthogonal to productivity in the corn sector, a result previously confirmed by McAloon et al. (2000) and Sarmiento et al. (2012). We infer from this evidence that the conditions for causal inference are satisfied.

To establish causality we exploit the fact that the EPA had no effect on demand for other closely-related agricultural commodities that cannot be used to produce ethanol. Of the commodities that might play this role soybeans are an obvious control group because they are produced in the same locations as corn, use similar production processes but due to their chemical composition cannot be used to manufacture ethanol. Diagnostic tests confirm that soybeans constitute a valid counterfactual and that the parallel trends assumption is met.

Given our focus on established producers we use difference-in-difference estimations that compare the evolution of productivity within the corn industry with soybean productivity in the same Midwestern county. Our research design takes several steps to eliminate endogeneity bias and ensure comparability between the treatment and control groups. For example, the regression equations include county-year fixed effects that rule out time-varying productivity and technological shocks common to both groups at both the local and macro levels. In addition, we include county-industry fixed effects that net out any time-invariant heterogeneity in the cross-section that differentially affects each industry. The average treatment effect (ATE) is therefore identified by cross-industry variation within the county-year dimension of the data set. This setup ensures that, conditional on covariates, the identifying assumption that the treatment and control groups are only randomly different holds.

An attractive feature of our data set is that we use physical-output based productivity variables. We use crop yields (the number of bushels of corn produced per acre), the stan-

[1] To maximize revenue ethanol producers sought out areas with high demand for distillers' dry grains, a by-product of ethanol production that can be used as an animal feed and accounts for 20% of revenues.

dard measure of physical productivity in the agricultural sector, and in addition, we construct physical total factor productivity (TFPQ) which measures output using physical quantities and accounts for input usage, including seed expenditures.[2] Unlike other approaches that use revenue and industry-level price deflators to measure output, our productivity measures do not capture confounding price effects or adjustments to market power that may make firms appear more productive even if underlying technical efficiency is unchanged. Rather, we exclusively study how the shock to demand affected technical efficiency.

Our estimates show that the demand shock caused a statistically significant increase in productivity among the treatment group relative to the implied counterfactual. Economically, the ATE equates to a 5.7% per annum increase in yield per acre. Consistent with the theoretical predictions we find that the productivity gains are driven by technical change. Following the demand shock corn producers rapidly adopted a new seed variety (stacked-variety corn seeds) that had been commercially available for several years but was seldom used. These represented an upgrading in the quality of inputs because they blended existing pest tolerance (Bt) and herbicide tolerance (Ht) genes into a single variety. Stacked-variety seeds produce more bushels per acre relative to these alternative single-gene (Bt or Ht) seed types by allowing the crop to get closer to its yield potential. Our estimates show that the demand shock caused a 17 percentage point increase in the share of acreage planted with stacked-variety seed post 2005. Pre 2005 the incidence of the stacked-variety seed was almost zero across the Corn Belt but rose rapidly following the demand shock, reaching 60% of planted acres in some regions. Notably, the estimated productivity increases that we find from our analyses are close in size to those found from field-trials of stacked-variety seed reported by the US Department for Agriculture (USDA) (Fernandez-Cornejo et al., 2014). Further support can be found from our estimates of the effect on TFPQ, where we find much smaller increases, and from studying other inputs including capital, labor and fertilizer, where there were no significant increases.[3] The smaller TFPQ effect is entirely consistent with the higher price of stacked-variety relative to single-gene seeds.

In subsequent tests we adopt a two-stage least squares approach to pin down the precise mechanisms identified by the model. From this exercise we find evidence that the productivity gains are indeed driven by technical change. A 10 percentage point increase in the stacked-variety share of acres causes an increase in productivity of around 4 bushels per acre. This exercise

[2] Foster et al. (2008) note that comparisons of TFPQ are more meaningful when variations in quality are small. This argument would appear to be relevant in the case of corn.

[3] Evidence from the agricultural literature suggests that these additional TFP effects arose because of other complementary changes to farming practices, in particular to tilage.

also allows us to quantify the relative importance of the demand and competition channels in motivating technical change. Although both mechanisms are found to significantly increase technical change, the direct effect of demand greatly outweighs the effect arising from increased competition due to a larger equilibrium number of firms. The comparatively small competition effect is consistent with the relatively high sunk costs of entering corn production and the intense ex ante level of competition within the corn sector.

Technical change and productivity improvements could derive from supply-side forces. For example, if the cost of stacked-variety seeds falls through time producers may adopt the more productive technology irrespective of demand conditions. The data decisively refute this view. First, the raw data show no reduction in the per acre cost of stacked-variety seed during the sample period. Rather, stacked-variety seeds are more costly compared to single-gene seeds and this relative price difference actually increased through time. Second, falsification tests show no evidence of significant productivity increases among corn producers located in Canada and Texas which were unaffected by the ethanol demand shock. Operating practices, seed availability and seed prices are similar in the Corn Belt and these regions. However, their location far from ethanol plants and the high associated transport costs meant that the ethanol boom did not affect demand for Canadian or Texan corn. If reductions in technology costs undergird our main results we should uncover productivity gains among corn producers in these regions of similar magnitude compared to in the Corn Belt. This is not the case.

Productivity could increase for other reasons. Such confounds include shocks to other sources of demand, climactic conditions during the growing season, changes in financial constraints, spillover effects on the control group and reallocation effects. We explore these alternative mechanisms but find little support for them in the data.

Literature review. Our paper is related to several strands of literature. Market size is often viewed as a prerequisite for productivity-enhancing investments such as innovation and technology adoption. Increases in actual or potential market size generate profit incentives that pull economic agents into new technological advances. Acemoglu and Linn (2004) formalize these ideas in a model of innovation where current and future market size shape the direction of innovation. Similarly, market size and profit incentives play a central role in most growth models featuring endogenous R&D-driven technological progress (e.g. Romer, 1990, Grossman and Helpman, 1991, Aghion and Howitt, 1992) and in models of technology adoption (e.g. Parente and Prescott, 1999). Papers in this line of research focus on the direct effect of market size on innovation and technological change/adoption, while the competition effect is absent.

In standard expanding variety and Schumpeterian growth models, increases in competition reduce innovation. Step-by-step models (Aghion et al., 2005) extend the Schumpeterian framework to include an 'escape competition' effect which generates a positive relationship between competition and innovation.[4] In this class of models there is no entry, some sectors are more competitive than others, and firms innovate to escape the highly competitive 'neck-and-neck' sectors. Since markups are fixed, changes in market size can affect competition only through a composition effect which operates through changes in the share of highly competitive sectors. Consequently, demand and any other shock cannot affect entry and markups within any sector of the economy. Desmet and Parente (2010) generate positive effects of competition on technical change in a monopolistically competitive model of technology adoption with Lancaster (1979) preferences. In this model, increases in the size of the market affect technology adoption only through the competition channel and a pure market-size effect is absent.

Our model complements these lines of research by providing an environment where demand drives technological progress through a direct market size channel, and an indirect channel operating through product market competition. It does so by departing from monopolistic competition, a market structure common to all the papers discussed above. Our model is closely related to a fairly unexplored class of innovation-driven growth frameworks under oligopoly pioneered by Peretto (1996) and recently developed by Impullitti and Licandro (2016). These models are designed to analyse the effects of increases in market size due to trade liberalization on innovation and growth in economies with variable markets. We use a simplified closed economy version of these models which is tailored to analysing the implications of demand shocks for productivity growth, and distinguishing the direct market size and the composition effects.

Early studies by Schmookler (1954) and Griliches (1957) identified market size effects as a key driving force behind both new inventions and technology adoption. Similarly Jaffe (1988) and Cohen and Klepper (1996) find a positive link between firm size and R&D intensity. There is a large empirical macro and trade literature studying the effects of market size on technological change. Several recent papers have found robust effects of trade-induced increases in market size on innovation and technology adoption. Bustos (2011) shows that MERCOSUR, a large regional trade agreement, had a strong impact on several measures of technical change at the firm level, including R&D, spending on technology transfers, and capital goods that embody new technologies. She finds that increases in revenue generated by tariff reductions lead exporters to innovate more. Lileeva and Trefler (2010) show that Canadian firms which experienced an increase in market size following the Canada-US Free Trade Agreement raised their labor

[4]See Aghion and Griffith (2005) for a survey of the theoretical and empirical work on competition and growth, and Acemoglu et al. (2016) and Akcigit et al. (2017) for recent applications.

productivity by investing in innovation and adopting new technologies. Griffith et al. (2010), find that the EU Single Market Programme (SMP), a large program deregulating the product market, is associated with increased product market competition and with increases in innovation and productivity growth. Aghion et al. (2017) analyse the effects of demand shocks generated by exports on innovation decisions of French firms. Similarly to our paper they find evidence of both a market size and a competition effect of export shocks on innovation. They show that firm patenting responds positively to export demand shocks and more so in more competitive sectors.

The paper is organized as follows. In the next section we outline the theory that guides our empirical analyses. In Section 3 we describe the data set. Section 4 provides an overview of the corn and ethanol industries and the key legislative changes that motivate our empirical framework. We outline our identification strategy and provide the main results in section 5. Section 6 contains an exhaustive set of robustness tests and in Section 7 we draw conclusions.

2 A simple model

We devise a simple model of endogenous technical change to highlight some key economic mechanisms which guide and help interpret our empirical findings. The model is a fully-fledged endogenous growth framework where better technologies are introduced through innovation. We choose this framework based on its generality, as it embeds a key set of channels through which demand shocks can affect technological progress and productivity growth.[5]

We draw upon Impullitti and Licandro (2016) and Peretto (1996). In the economy there is a contiuum of product lines, each producing a variety of a differentiated good. Each variety is produced by a small number of firms engaged in Cournot competition for market share. Individual firms are therefore "large in the small but small in the large", meaning that they have market power in the their own product line, but they are infinitesimal in the economy as a whole. This allows us to embed oligpoly models in general equilibrium thereby overcoming some of the technical problems present in these models (Neary, 2003). Firms have access to an innovation technology which allows them to increase their productivity over time. The innovation technology features standard knowledge spillovers which lead to sustained long-run growth. We choose this type of model because it allows an easier formalization of innovation

[5]The model is broader than the specific case we analyse in the empirical section. A two-period versionl where technical change is not a continous process but simply involves a one shot decision to pay a sunk cost and acquire a better technology would represent more literally the specific case of the corn industry analysed in the empirical section. However, the transmission mechanisms through which demand shocks affect productivity would not change in a technology adoption version of the model.

by incumbent firms, which is the type of innovation that we test for empirically.[6] Moreover, in oligopoly models with entry market structure responds to policies, thereby generating new transmission channels.

2.1 Economic environment

The economy is populated by a unit mass of identical consumers endowed with a unit flow of labor that is supplied inelastically. Households have the following preferences,

$$U = \int_0^\infty (\ln X_t + \beta \ln Y_t)\, e^{-\rho t} dt.$$

where Y is a homogeneous good and X is a differentiated good composed of a continuum of varieties according to

$$X_t = \left(\int_0^1 x_{jt}^{\alpha}\ \mathrm{d}j \right)^{\frac{1}{\alpha}}, \tag{1}$$

where x_{jt} is variety j, and $1/(1-\alpha)$ is the elasticity of substitution across varieties, $\alpha \in (0,1)$.

The homogeneous good is produced using labour with unit cost of one, and is the numeraire of our economy. In each product line j there are n firms producing a perfectly substitutable version of the variety with the same productivity. Firms produce each variety with technology

$$q_{jt} = \tilde{z}_{jt}^{\eta} l_{jt}, \tag{2}$$

where $\tilde{z}$ is a measure of productivity, l represents labor and q production. In every period, firms devote labour resources to improve their technology according to the technology frontier,

$$\dot{\tilde{z}}_{jt} = A k_{jt} h_{jt}, \tag{3}$$

where h_{jt} is labor, $A > 0$, and k_t represents knowledge spillovers defined as

$$k_{jt} = \ \tilde{z}_{jt}^{c}, \tag{4}$$

where $\tilde{z}^c$ is the productivity of the other $n-1$ firms in each product line. This specification embeds the typical knowledge spillovers which sustain endogenous growth. We assume that

[6] In both the expanding variety endogenous growth model (Romer, 1990), and in Schumpeterian growth models (Aghion and Howitt, 1992) innovation is performed by entrants. Introducing innovation by incumbents in Schumpeterian models is possible but complicates the framework substantially.

initial productivity is the same for all product lines and in the symmetric equilibrium that we will derive below productivity will also be the same for all firms within a product line.

2.2 Equilibrium

Next, we characterize the steady state equilibrium of the model.

Households. The household problem is straightforward and yields equilibrium conditions,

$$Y = \beta E \tag{5}$$

$$\frac{\dot{E}}{E} = r - \rho \tag{6}$$

$$p_{jt} = \frac{E}{X_t^{\alpha}}\, x_{jt}^{\alpha-1}, \tag{7}$$

where r is the interest rate, p_{jt} is the price of good j, and $E = \int_0^1 p_{jt}x$ is total expenditure on the composite good X. For variables that are constant in the steady state, such as r, Y, and E index t is omitted to simplify notation. Total spending on the homogeneous good is β times total spending on the differentiated good. Equation (6) is the standard Euler equation implying $r = \rho$ in the steady state, and (7) is the inverse demand function for variety j.

Firms' problem: Cournot equilibrium. The n firms competing in the production of each variety j play a dynamic Cournot game. We characterize the open loop Nash equilibrium of this game. At time s a firm producing a particular variety solves (we suppress index j to simplify notation)

$$V_s = \max_{\{q_t, h_t\}]_{t=s}^{\infty}} \int_s^{\infty} \Big((p_t - \tilde{z}_t^{-\eta})q_t - h_t - \lambda \Big) \mathrm{e}^{-\rho(t-s)}\ \mathrm{d}t, \qquad s.t. \tag{8}$$

$$p_t = \frac{E}{X_t^{\alpha}}\, x_t^{\alpha-1}$$

$$x_t = \hat{x}_t + q_t$$

$$\dot{\tilde{z}}_t = Ak_t h_t$$

$$\tilde{z}_s > 0,$$

where profits are discounted at the steady-state interest rate ρ. The first constraint is the demand function for the variety; the second states that the total market for each variety is split between this particular firm and its direct $(n-1)$ competitors. The third constraint is the innovation technology. In solving this problem the firm takes its competitors' production $\hat{x}_t$, the externality k_t and the aggregate variables E and X_t as given.

Firms are assumed to face the same initial conditions, resulting in a symmetric equilibrium with $x_t = nq_t$. As shown in the Appendix, solving the problem of the firm yields the following demand for variable inputs

$$\tilde{z}_t^{-\eta} q_t = \theta e, \tag{9}$$

where $e \equiv E/n$ is expenditure per firm. The equilibrium growth rate of productivity is

$$g \equiv \frac{\dot{\tilde{z}}}{\tilde{z}} = \eta A \theta e - \rho, \tag{10}$$

and equilibrium innovation for firm z is

$$h = \eta \theta e - \frac{\rho}{A}. \tag{11}$$

Equations (10) and (11) show that larger market size (sales per firm) lead to higher innovation and growth. Similarly, a more competitive economy, represented by a lower markup, $1/\theta$, implies higher innovation and growth.

Market clearing. Labor market clearing closes the model. The labor endowment is allocated to production and innovation activities in the composite sector, and to production in the homogeneous sector,

$$n \int_0^1 (l_j + h_j) \, \mathrm{d}j + Y = n \int_0^1 \left(\tilde{z}_j^{-\eta} q_j + h_j \right) \, \mathrm{d}j + \beta E = 1.$$

Using the equilibrium quantities and innovation decisions derived above labor market clearing becomes

$$e = \frac{\frac{1}{n} + \frac{\rho}{A}}{\beta + (1+\eta)\theta}, \tag{MC}$$

which pins down equilibrium expenditure per firm e.

Proposition 1 *An increase in demand for the differentiated goods increases expenditure per firm e and raises innovation and productivity growth.*

From (MC) it is easy to see that a reduction in β, which generates an increase in the demand for differentiated goods, leads to greater market size for each firm, e. Equations (10) and (11) show that higher market size trigger innovation and faster growth. Intuitively, since the benefits of cost-reducing innovation are increasing in the quantity produced, but the innovation cost does not scale with production, a larger market size increases the incentives to innovate. The increase in resources allocated to production and innovation in the differentiated goods sector is feasible since the demand shock diverts resources away from the homogeneous good.

Free entry. Here we show that introducing free entry does not change the results and adds a further testable mechanism. Let us assume that in each product line firms can enter paying a sunk cost ϕ. Equalizing profits to the cost of entry we obtain the following free entry condition,

$$e = \frac{\rho\phi - \frac{\rho}{A}}{1 - (1+\eta)\theta}. \tag{FE}$$

This condition together with (MC) determines the equilibrium expenditure per firm e and number of firms per product line n.

Proposition 2 *An increase in the demand for the differentiated goods increases expenditure per firm e, increases the number of firms per product line n, reduces the markup $1/\theta$, and raises innovation and productivity growth.*

The proof is straightforward and we leave it to the appendix. Here we briefly discuss the economic intuition. The demand shock has identical effects working through a similar mechanism as in the case without free entry. The additional result is that, a demand shock, by increasing the size of the market stimulates entry, thereby leading to a larger equilibrium number of firms and lower markups. The increase in product market competition that follows leads to a further increase in the effective market size per firm θe. Equation (9) shows that variable costs, and therefore the quantity produced by each firm is proportional to both expenditure per firm and the inverse of the markup, θ. Hence, higher product market efficiency leads to lower markups which increases the quantity produced and ultimately stimulates firms to innovate more. Again this increase in market size is feasible because market shares are reallocated from the homogeneous good toward the differentiated good.

3 Data

We retrieve productivity data from the National Agricultural Statistics Service (NASS) - the statistics branch of the USDA. Each year the NASS conducts hundreds of detailed surveys on agricultural industries. As part of this mission it collects information on crop yields (bushels per acre), the dominant measure of productivity within agriculture, in industry i in county c during year t. We therefore have annual productivity data for the corn and soybean industries within each county-industry over the period 2000 to 2010. In total the sample contains 18,092 observations, drawn from 1,003 counties located in the 12 states that form the Corn Belt.[7] The decision to restrict the sample to the Corn Belt is predicated on the fact that both the corn and ethanol industries are geographically concentrated in the region: 88% of national corn and 93% of ethanol production takes place in the Corn Belt. Further information on acres planted, the number of firms and irrigation (the ratio of irrigated acreage to total acres) for each county-industry-year is taken from the NASS.

In the empirical analysis we also use physical total factor productivity (TFPQ) which accounts for input use and measures output in physical quantities (bushels per acre in this case). A key advantage of both the yield and TFPQ variables is that changes in productivity cannot be driven by price shocks, market power, factor market distortions or changes in the product mix which frequently contaminate productivity estimates when revenue is used to measure output and firm-level price data are unavailable.

One constraint we face in constructing TFPQ in the corn and soybean industries is that the NASS does not release data on capital stocks, labor, material, and energy inputs at the county-industry level. However, annual state-industry level information is available from the ERS Agricultural Resource Management Survey (ARMS). Following Foster et al. (2008), TFPQ is constructed using the typical index form

$$tfp_{ist} = y_{ist} - \alpha_k k_{ist} - \alpha_l l_{ist} - \alpha_m m_{ict} - \alpha_e e_{ist}, \tag{12}$$

where i, s and t denote industry, state and year, respectively; the lower-case letters indicate the natural logarithm of output, capital stock, labor hours, material inputs, and energy inputs, and α_j ($j \in (k, l, m, e)$) are the corresponding factor elasticities. All inputs and output are measured per acre. Labor inputs are measured in hours, capital as the value of machinery services used, and material inputs are the sum of expenditures on fertilizer, lime, seeds, herbicide and insecticide. We deflate capital, material, and the other inputs into 1992 values using their respective NASS input price index. That is, we have a separate price index for each input. Recent work by De Loecker et al. (2016) highlights the problem of unobserved input prices in the context of

[7]The 12 states in the sample are Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin.

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max	Level of Aggregation	Data Source
Yield	18,092	89.86	53.68	10.40	203	County	NASS
TFPQ	165	0.20	0.04	0.08	0.26	State	Authors calculations
Ethanol capacity	18,092	3.04	6.64	-9.21	8.68	County	Authors calculations
EPA	18,092	0.27	0.44	0	1	County	Authors calculations
Firms	18,092	0.11	0.12	0	1.03	County	NASS
Acres planted	18,092	72.02	57.27	0.50	541	County	NASS
Irrigation	18,092	6.73	20.53	0	100	County	NASS
GE share	264	69.23	24.35	9	98	State	ARMS
Land and buildings	128	0.64	0.53	0.01	1.81	State	ARMS
Machinery and equipment	128	0.13	0.11	0.01	0.40	State	ARMS
Rented machinery	128	0.30	0.23	0.01	1.06	State	ARMS
Labor	128	5.04	3.96	0.02	13.85	State	ARMS
Fertilizer	128	22.26	17.47	0.01	62.62	State	ARMS
GE cost	126	0.19	0.15	0.01	0.60	State	ARMS
Exports	18,092	5.60	4.79	1.75	18.56	Industry	ARMS
Food	18,092	1.36	0.06	1.22	1.45	Industry	ARMS
Feed	18,092	5.63	0.40	4.79	6.14	Industry	ARMS
MTBE	18,092	0.09	0.28	0	1	State	EIA
Entry rate	15,134	21.95	11.98	0	103.65	State	Census
Banks	18,092	7.95	7.48	1	171	County	SNL Financial
Temperature	18,092	2.97	0.67	0.05	47.56	County	Weather Underground
Precipitation	18,092	2.64	1.24	0	8.80	County	Weather Underground
Output (ln)	8,209	15.49	1.47	8.70	18.16	County	NASS
DDGs demand	8,209	0.01	0.03	0	0.66	County	NASS
Plants within 100 miles	8,209	6.21	6.67	0	39	County	Authors calculations
Plants within 200 miles	8,209	22.67	19.49	0	86	County	Authors calculations
Capacity within 100 miles	8,209	292.81	382.14	0.0001	2,847	County	Authors calculations
Capacity within 200 miles	8,209	1,085.76	1,084.40	0.0001	5,856	County	Authors calculations
Entry	8,209	0.17	0.37	0	1	County	Authors calculations
Capacity under construction	8,209	0.04	0.18	0	1	County	Authors calculations

Notes: This table provides summary statistics on the dependent and independent variables used in the empirical analysis.

productivity estimation and the associated difficulty in identifying the underlying drivers of productivity growth. By using input-specific price indexes we overcome these issues. To construct the labor, material, and energy input elasticities, we use industries' average cost shares over our sample. Capital cost shares are measured as the capital stock (the sum of farm equipment, land and buildings) multiplied by the capital rental rates reported by Duffy (2010).

Information on technical change is also taken from the ARMS database. This source provides annual data on the share of acres planted using stacked-variety seeds (the ratio of acres planted with stacked-varieties to total acres) for each state-industry between 2000 and 2010. Corn producers have access to two types of corn seed. Single-gene varieties are GE seeds that contain genetic traits that either protect the plant from herbicide poisoning or pests (Ht or Bt). Stacked-variety seeds combine both traits in each seed. Experimental trials have consistently shown stacked-varieties to produce higher yields per acre by preventing destruction of the crop. However, stacked-varieties typically retail at a premium to traditional seeds as shown in Appendix Table A.1. Both types of seed were commercially available throughout the sample period.

We match the productivity and technical change data to information on the ethanol industry taken from *The Ethanol Industry Outlook*, an annual industry journal published by the Renewable Fuels Association. This contains annual plant-level data on the owner, capacity (operating and under construction), location, and feedstock of every ethanol plant in the US. We exclude all plants that do not use corn as a feedstock on the grounds that they are irrelevant to corn producers.

The remaining variables used in the econometric analysis are listed in Table 1. This includes the number of banks in each county (SNL Financial), various types of input usage (ARMS), precipitation and temperature, measured by growing degree days over the growing season (Weather Underground).[8] A complete description of each variable is provided in Appendix B.

4 Overview of the Corn and Ethanol Industries and Legislative Changes

In this section we outline important details regarding the production and distribution of ethanol, as well as the key reforms to US energy policy that sparked the ethanol boom.

[8]We match each county to the nearest weather station because not all counties contain a weather station.

4.1 The Ethanol Production and Distribution Process

Ethanol is a clean-burning, high-octane motor fuel. Almost all ethanol is derived from starch- and sugar-based feedstocks. The ease with which these sugars can be extracted from corn makes it the preferred feedstock of large-scale, commercial ethanol producers (USDE, 2013).[9] The production process involves converting starch-based crops into ethanol either by dry- or wet-mill processing. More than 80% of ethanol plants in the US are dry mills due to lower capital costs (McAloon et al., 2000; USDE, 2012). During the dry-milling process the corn kernel is ground into flour and subsequently fermented to make ethanol. By-products of this process include distillers dry grains (DDGs), which can be sold as animal feed. Wet-mill plants steep corn in a dilute sulfuric acid solution in order to separate the starch, protein, and fiber content. The corn starch component can then be fermented into ethanol through a process similar to that used in dry milling, while the steep water is sold as a livestock feed ingredient.

Corn accounts for approximately 60% of ethanol production costs, with the remainder attributable to natural gas (15%), other variable costs (12%), and fixed costs (13%) (Hofstrand, 2013). The distribution process entails shipping harvested corn from farms and co-ops to ethanol plants using lorries which are the low-cost transport option (McNew and Griffiths, 2005; Fatal, 2011). Tanker trucks and rail cars are subsequently used to transport manufactured ethanol to a terminal for blending. The blended gasoline is then distributed to gasoline retailers or stored.

4.2 Legislative Changes

The origins of the ethanol boom lie in a series of political issues that culminated in the 2005 EPA. During the early 2000s a perception grew within national policymaking circles that the US economy was overly reliant on foreign energy supplies that were vulnerable to interruption (Diggs, 2012). In response to these pressures, the EPA aimed to improve national energy independence and security by stimulating various forms of domestic energy production. Part of this legislative agenda sought to displace crude oil imports and reduce reliance on foreign energy sources by promoting greater use of ethanol in gasoline. The EPA mandated a rise in the ethanol content of gasoline from 4 billion gallons in 2006 to 7.5 billion in 2012. In addition, the EPA set a target, known as the Renewable Fuel Standard (RFS), that a minimum 10% of gasoline should be made-up of ethanol in future.[10] The subsequent Energy Independence and Security

[9] According to USDE (2013) over 90% of US ethanol production relies on corn as a feedstock. Owing to differences in their chemical properties, multiple feedstocks cannot be mixed together during production.

[10] The USDA Feed Grains Database reports that by 2009 the ethanol market share of the US gasoline industry had reached 8% as a result of the energy legislation.

Act of 2007 set yet higher targets, mandating a minimum 36 billion gallon ethanol content by 2022.

4.3 The Ethanol Boom

The volumetric ethanol production targets and the RFS provided surety of ethanol demand. Ethanol producers also benefitted from a 51 cent per gallon tax credit paid through the Volumetric Ethanol Excise Tax Credit (VEETC), and were shielded from competition with foreign ethanol producers by an import tariff of $143/m^3 levied on imported ethanol.[11] Because older (post-1992) and newer (post-2001) vehicles did not require engine modifications to run on blended ethanol, most gasoline retailers throughout the US began to offer E10, a fuel mixture of 10% ethanol and 90% gasoline. Automobile manufacturers also promoted blended gasoline by introducing car engines capable of running on E15 and E85.[12] Following successful engine performance tests, the US Environmental Protection Agency authorized the use of blended gasoline in all motorcycles, heavy-duty vehicles, and non-road engines (for example, motorboats).

Figure A.1 in the Appendix illustrates the wave of investment in new ethanol plants, and the geographical concentration of entry on the Corn Belt. Entrants account for 76% of capacity expansion during the sample period. Table 2 provides further detail on these patterns. Between 2002 and 2010 the number of ethanol plants increased from 76 to 199 and capacity increased by almost 300%. Much of this entry occurred in the two years after implementation of the EPA when the net entry rate spiked to 33% and 53%. The average plant operating capacity is 56 million gallons per year (mgy) and there is an upward trend in this average (48 mgy in 2002 versus 63 mgy in 2010), reflecting the entry of larger plants and capacity expansions.[13]

Figure 1 documents the increasing importance of the ethanol sector as a source of the demand for corn following enactment of the EPA. During the years prior to 2005 approximately 11% of national corn production was used to manufacture ethanol. Following the expansion of ethanol production capacity this value steadily increased to 40% by 2010. In addition, Appendix Figure A.3 shows that the increase in ethanol demand did not displace other sources of corn demand

[11] The VEETC was created under the American Jobs Creation Act of 2004. It was renewed as part of the Farm Bill of 2008 at a lower rate of $0.45 per gallon of ethanol blended with gasoline.

[12] Auto manufacturers that introduced models with E85 compatible engines included Audi (A4), Bentley (Flying Spur), Buick (Lacrosse, Regal, Verano), Cadilac (Escalade), Chevrolet (Captiva, Equinox, Impala, Malibu, Silverado), Chrysler (200, 300 AWD, Town and Country), Dodge (Avenger, Challenger, Charger, Dart, Ram Tradesman), Ford (Expedition, Explorer, F150, Focus, Taurus), GMC (Savanna Van, Yukon), Jeep (Grand Cherokee), Lincoln (Navigator), Nissan (Armada, Titan), Toyota (Tundra). The price of these vehicles was not substantially different from non-E85 engine vehicles, ranging between $15,995 (Dodge Dart) to $184,300 (Bently Flying Spur). For further details see e85vehicles.com.

[13] 3.5 billion gallons of ethanol were contained in gasoline in 2004, compared to 13.3 billion gallons in 2010. Appendix Figure A.2 shows that the market share of ethanol imports is close to 0 in all years.

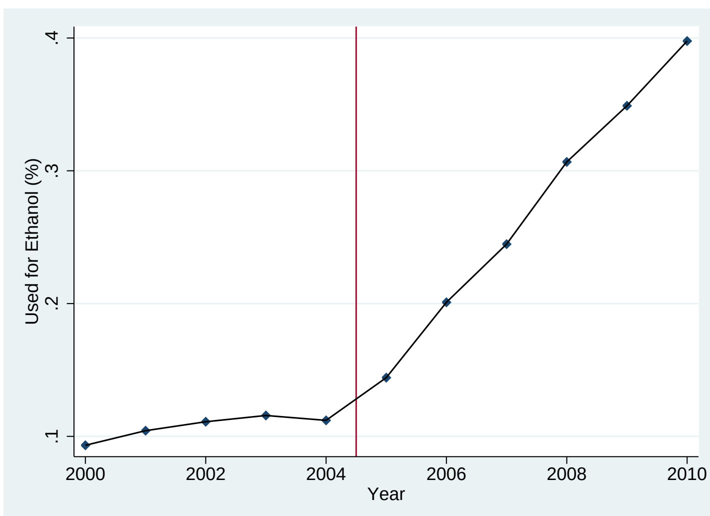
such that demand for corn was strictly higher after 2005.

Table 2: Ethanol Industry Evolution

Year	Plants	Net Entry (%)	Capacity (mgy)	Multiplant (%)	Corn Belt (%)
2002	60		1312	30	92
2003	67	11.67	1489	27	93
2004	76	13.43	1863	24	94
2005	87	14.47	2453	21	93
2006	116	33.33	2951	25	92
2007	177	52.59	3860	21	86
2008	188	6.21	4344	43	81
2009	201	6.91	6323	41	84
2010	199	-1.00	7325	37	84

Notes: This table provides information on the number of ethanol plants, the net entry rate, operating capacity in the industry (in mgy) for each year of the sample. Multiplant is the percentage of plants within the industry that belong to a multi-plant firm. The variable Corn Belt is the percentage of ethanol plants located in the 12 states that comprise our sample. *The Ethanol Industry Outlook* does not provide plant-level data before 2002.

Figure 1: Share of US Corn Used to Produce Ethanol



Notes: This figure plots the annual percentage of national corn production used to manufacture ethanol between 2000 and 2010. The data are taken from the USDA Feed Grains Database. The vertical line represents the beginning of 2005, the year when the EPA was signed into law.

5 Empirical Results

In this section we outline the empirical strategy we use to pin down the effect of demand on productivity and technical change. We then proceed by testing the theory's key predictions.

5.1 Identification Strategy

Isolating causality revolves around a difference-in-difference estimation strategy. We estimate the equation

$$y_{ict} = \alpha_{ic} + \beta Corn_{ic} * Post_t + \delta X_{ict} + \gamma_{ct} + \varepsilon_{ict}, \tag{13}$$

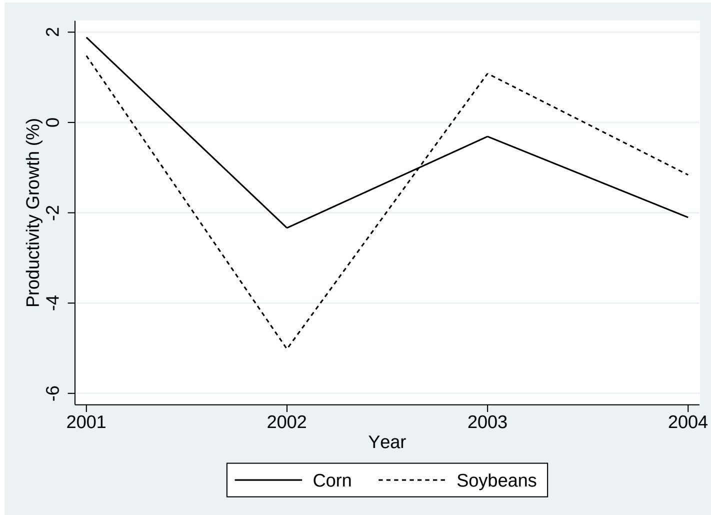
where y_{ict} is an outcome variable (productivity or technical change) in industry i in region c (either a county or state) at time t; $Corn_{ic}$ is a dummy variable equal to 1 if the observation is from the corn industry, 0 otherwise. We measure demand using the standard difference-in-difference dummy variable that captures the passing of the Energy Policy Act in 2005 where $Post_t$ is a dummy variable (capturing the demand shock) equal to 1 for the years 2005-2010, 0 otherwise. We also experiment with a continuous demand measure, ethanol capacity, which captures ethanol production capacity within 200 miles of the county. The choice of 200 miles is based on estimates from the agricultural economics literature, which suggests that ethanol producers procure corn from farms within this range to ensure timeliness of supply and, because ethanol manufacturers bear the transport expenses, to minimize shipping costs (Hofstrand, 2013; McAloon et al, 2000; Sarmiento et al., 2012; USDE, 2013).

The regressions include a vector of control variables, X_{ict}, while ε_{ict} is the error term. We also include a full set of region-year (γ_{ct}) and region-industry (α_{ic}) dummy variables to soak up unobserved heterogeneity. In the productivity (technical change) tests the region is defined as a county (state). Region-year effects capture all time-varying productivity/technological determinants that are common to both groups and coincide with treatment (such as climatic shocks or adjustments to tax rates). This tight focus provides an ideal estimating environment because the ATE is identified through cross-industry variation within the region-year dimension of the data. To purge time-invariant productivity/technical change determinants that are region-specific, but differentially affect the dependent variable within the treatment and control groups, we include region-industry effects.[14] We cluster the standard errors at the region level in line with Bertrand et al. (2004).

Central to this approach is establishing an implied counterfactual. We choose the soybean industry because soybeans cannot be used to produce ethanol. However, soybeans are ubiquitous throughout the Corn Belt, use similar production process as corn and are planted and harvested at the same time as corn meaning they are subject to similar climactic conditions over the growing season. For these reasons the soybean industry is an ideal control group.

[14]For example, soybean yields are affected to a greater extent by high soil pH values because this causes cyst nematode and brown stem rot.

Figure 2: Pre-Treatment Productivity Evolution



Notes: This figure plots the average rate of productivity growth within the corn and soybean industries during the pre-treatment period.

Table 3: Parallel Trends Test

Year	Corn	Soybeans	Difference	t-statistic
$\Delta Yield_{2004}$	-2.1031	-1.1614	0.9417	0.44
	(2.11)	(0.29)	(2.13)	
$\Delta Yield_{2003}$	-0.3104	1.0832	1.3936	0.81
	(0.33)	(1.69)	(1.72)	
$\Delta Yield_{2002}$	-2.3354	-5.0169	-2.6816	-0.56
	(3.69)	(3.07)	(4.80)	
$\Delta Yield_{2001}$	1.8851	1.4779	-0.4072	-0.18
	(1.89)	(1.15)	(2.21)	

Notes: $\Delta Yield_t$ denotes the annual rate of productivity growth measured as $(yield_t - yield_{t-1})/yield_{t-1}$. Standard errors are reported in parentheses. The t-statistic tests for equality between the productivity growth rate in the treatment and control groups at the 5% level.

The key identifying assumption underlying our tests is the parallel trends assumption. Figure 2 plots the annual rate of productivity growth in the corn and soybeans industries during the pre-treatment era. The patters are very similar, although corn productivity grew somewhat faster between 2002 and 2003. The important question is of course whether these trends are significantly different. We therefore use t-tests that test for equality between the productivity growth rates across the sectors in each year. These results are reported in Table 3. We find no significant differences for any of the years indicating that the parallel trends assumption is satisfied, and soybeans represent a valid counterfactual.

5.2 Econometric Results

Before reporting formal empirical tests of the demand-productivity relationship, we provide some descriptive evidence on the suggestive patterns within the raw data. In Figure 3 we compare the productivity distribution in 2000 to the situation in 2010 when the demand shock has had its fullest effect. There is a clear unambiguous increase in average industry productivity with a large rightward shift in the survival productivity threshold.[15] Appendix Figure A.5 provides clear evidence across all states in the sample that the passing of the EPA coincides with the steep section of the familiar S-shaped technology adoption function. The evidence reported in Figure 4 affirms that demand conditions lie at the heart of our findings. Specifically, the figure illustrates that technical change is positively correlated with local ethanol capacity, a strong proxy for demand.[16]

Turning to the more formal estimates, Table 4 reports estimates of equation (13) that provide evidence that the demand shock caused a significant increase in productivity within the corn industry. Column 1 of Table 4 reports estimates from a simple difference-in-difference model based on equation (13) without any control variables. The effect is economically meaningful and highly statistically significant. The ATE is estimated to be 7.25 bushels per acre, equivalent to a 5.7% increase in annual productivity compared to the pre-treatment mean.[17]

In column 2 of Table 4 we add as controls the number of acres planted and the incidence of irrigation technologies. The number of acres planted captures the possible effects of increasing or decreasing returns to scale. For example, farmers may make productivity investments following the demand shock but they might also cultivate increasingly marginal land which would tend to attenuate the ATE.[18] We find a positive and statistically significant correlation. Increasing the incidence of irrigation is also estimated to significantly raise productivity. The addition of these controls does little to alter the estimated effect of the EPA on yield per acre.

Central to the empirical strategy is the claim that the demand shock was due to the expansion

[15] Figure A.4 in the Appendix reports the distribution of productivity in 2000 and 2010 taking into account year effects. This ensures that the patterns in the data do not simply represent trends towards higher productivity through time. The evolution of productivity is very similar.

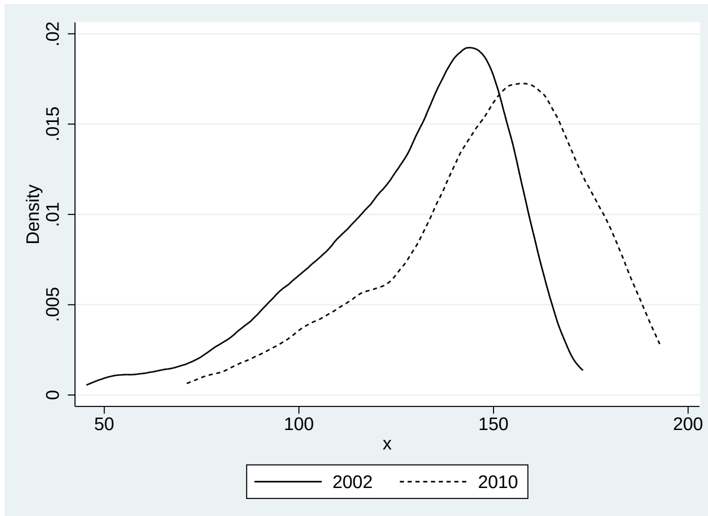
[16] The correlation is also highly statistically significant. Correlation = 0.40 (p-value = 0.00).

[17] Average corn productivity pre-2005 is 128 bushels per acre implying that the ATE is equivalent to 5.7% (7.25/128)

[18] Evidence from the literature indicates that, because ethanol plants were primarily located in the Corn Belt, the increase in the number of acres of corn that were planted within each county was economically small. Fatal (2011) finds a positive effect on corn acreage up to 286 miles from ethanol plants. He estimates that a new 100 mgy ethanol plant increased corn acreage by just 0.52%, and that the increase in a county's acreage of corn that occurred would supply just 0.21% of the total ethanol capacity of the new ethanol plant. For producers close to new ethanol plants the incentive was to make existing land more productive rather than convert acreage to growing corn.

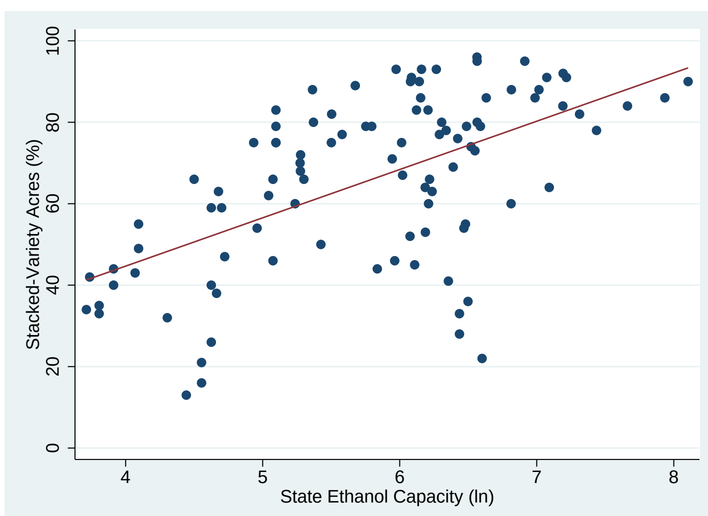
of the ethanol industry. To verify that changes in market size drive our inferences, we interact

Figure 3: Productivity Response to the Demand Shock



Notes: This figure shows kernel density plots the distribution of yield per acre in the corn industry in 2000 and 2010.

Figure 4: Ethanol Demand and Technical Change



Notes: This figure plots the share of corn acres planted with stacked variety seeds against ethanol capacity in each state-year.

Table 4: The Effect of Demand on Productivity and Innovation

Regression no.	1	2	3	4	5	6	7	8	9	10
Dependent variable	Yield	Yield	Yield	GE share	GE share	Yield	Yield	Yield	TFPQ	TFPQ
Panel A - Main results										
Corn * Post	7.2547***	6.6664***		16.9899***					0.0287*	
	(23.77)	(19.72)		(3.53)					(2.34)	
Corn * Ethanol capacity			0.5042***		2.6204**					0.0020***
			(18.03)		(2.92)					(3.82)
Acres planted		0.0654***	0.0892***	0.0034*	0.0080***	-0.0592***	-0.0596***	-0.0596***	-0.0022	0.0009
		(5.93)	(7.93)	(1.92)	(7.09)	(-5.58)	(-5.60)	(-5.62)	(-0.82)	(0.31)
Irrigation		0.1019***	0.0971***	0.8187*	0.8603	0.0415**	0.0414**	0.0414**	-0.0000**	-0.0000***
		(3.87)	(3.79)	(1.88)	(1.60)	(2.44)	(2.44)	(2.44)	(-2.64)	(-5.32)
Stacked variety share						0.3856***	0.3874***	0.3878***		
						(21.77)	(22.25)	(23.20)		
Panel B - Dependent variable: GE share										
EPA						19.4445***	18.5445***	16.8956***		
						(63.61)	(49.05)	(41.10)		
Firms							0.0149***	0.0101***		
							(4.25)	(3.02)		
EPA * Firms								0.0133***		
								(11.73)		
Kleibergen-Paap F-statistic						4,046	2,110	1,473		
Hansen J-statistic p-value							0.15	0.35		
N	18,092	18,092	18,092	264	264	18,092	18,092	18,092	165	165
R^2	0.98	0.98	0.98	0.91	0.89	0.21	0.21	0.21	0.83	0.88
County-industry effects	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No
County-year effects	Yes	Yes	Yes	No	No	Yes	Yes	Yes	No	No
State-industry effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
State-year effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes

Notes: County-level data is used in regressions 1-3, 6 and 7. State-level data are used in all other columns. The first-stage regression in columns 6-8 report estimates of equation (14). The standard errors are clustered at the county level in all regressions except in columns 4, 5,9 and 10 where they are clustered at the state level. t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

the corn dummy variable with the ethanol capacity variable. The estimates in column 3 of Table 4 show that a 10% increase in local ethanol capacity causes a 0.05 bushel per acre increase in corn productivity. Using the distribution of the change in ethanol production capacity within 200 miles of the county between 2004 and 2010 the value at the 25th percentile was 151 mgy. At the 75th percentile it was 4,046 mgy. These values imply an increase in capacity of 27% and 711% respectively, and in turn a 0.38% and 9.95% increase in the annual rate of corn productivity growth.[19]

In the remaining columns of Table 4 we tie the passing of the EPA and the increase in ethanol capacity with technical change. In columns 4 and 5 we study the increase in the share of acreage planted with stacked-variety corn seed. In columns 6 to 8 we then connect the increase in yield with the increased use of the stacked-variety technology using an instrumental variable approach. To construct these instruments we take seriously the theoretical model developed in Section 2 and use as instruments the passing of the EPA alongside the number of firms in the county as instruments. These capture the direct and indirect effects of an increase in demand on technical change. Finally, in columns 9 and 10 we explore whether the increased use of the advanced seed technology is associated with an increase in the productivity of land or whether there were also changes in TFPQ. If technology adoption is a key part of the change that occurred in the corn industry over this time period, then once we control for the additional seed expenditure due to switching to stacked-varieties, and which led to the change in yields, then there should be little or no change in TFPQ unless there are spillovers from the use of this technology.

A pattern of results emerges from the table that is consistent with a view that technical change was a key feature of the developments that followed from the shock to the demand for corn. Exploiting the incidence of stacked-variety corn seeds in total acreage from the ARMS data set, in column 4 of Table 4 we find that the EPA caused a 17 percentage point increase in the share of acres planted with stacked-variety seeds. Discussions by the USDA indicate that before 2005 stacked-variety seeds accounted for only 3% of planted acres, but were rapidly adopted post-2005, reaching an incidence of between 40% and 60% in most states by the end of the sample period (see Figure A.5). We find similar positive effects when we replace the EPA dummy with a continuous measure of ethanol capacity in column 5 of Table 4.

The instrumental variable approach captures the variation in corn productivity that is explained by technology adoption. In the first stage we use the share of acres planted using

[19]This finding is robust to defining the local market using a 100 mile radius.

stacked-variety seeds as the dependent variable and estimate the equation

$$SV_{ist} = \alpha_{is} + \varphi_1 EPA_{ist} + \varphi_2 Firms_{ist} + \varphi_3 EPA_{ist} * Firms_{ist} + \delta X_{ist} + u_{ist}, \qquad (14)$$

and use the predicted value of SV_{ist} in the second stage regression

$$yield_{ict} = \alpha_{ic} + \beta \hat{SV}_{ist} + \theta X_{ict} + \gamma_t + \nu_{ict}. \qquad (15)$$

In equation (14) EPA_{ist} is a dummy variable equal to 1 if an observation is drawn from the corn industry from 2005 onwards, 0 otherwise. The direct effect of demand on technical change is captured by φ_1. Given our model predicts that demand triggers technical change by provoking an increase in the number of firms we interact the demand and number of firms variables. This indirect effect is captured by φ_3.

The first stage regressions from the IV approach in columns 6 to 8 show that demand alongside the number of firms have the expected relationship with technical change and collectively pass the standard tests for weak and valid instruments. These first stage regressions also suggest that the direct effect of demand shocks explain the majority of the technical change that occurred. The effects that comes through changes in the number of firms, whilst present, is much smaller in magnitude. On average, the results in column 8 imply that the equilibrium number of firms would need to increase by almost 1,270 to have the same effect on technical change as the direct effect of demand. The instruments also pass the overidentification test, indicating that our instruments are uncorrelated with the error term. The Kleibergen-Paap F-test results indicate that we cannot reject the null hypothesis that the instruments are jointly valid.[20]

The coefficient estimate on the stacked-variety share in the second stage regression is also statistically significant and positive. The estimates in column 8 show that a 10 percentage point increase in the use of stacked-variety corn seeds increases yields by 3.9 bushels per acre. Using the increase in stacked corn acreage of between 40% and 60% this would imply an increase in yields of between 15 and 23 bushels per acre, or 12% and 18% on pre-treatment means. To put this in a broader context, data from the ARMS survey shows that field trials on single-gene corn seeds have an average yield of 134 bushels per acre, whereas stacked-varieties on average yield 171 bushels per acre. This is an increase of around 27% compared to single-gene seeds, which is close to the estimates of yield increases we derive elsewhere in the paper.

Finally, in the rest of Table 4 we include regressions in which TFPQ is the dependent variable

[20] The results are unchanged in regressions which use the continuous demand variable instead of the EPA_{ist} dummy variable.

in equation (13). Here we find that the EPA had only a small effect, an increase of just 2%. The small TFPQ response relative to the increase in yield found elsewhere in the table is consistent with the argument above that when we account for the increase in seed expenditure when calculating TFPQ, the improvement in TFP is small. The agricultural economics literature discusses other sources of productivity gains that have followed from experience in the use of stacked-variety seeds. Of some importance appear to have been reduced tillage requirements. Reductions in the number of times farmers needed to till the soil led to reduced fertilizer run-off and lower gasoline costs, leading to higher TFPQ.

6 Threats to Identification

Before we can conclude that demand shocks improve productivity causally, we need to rule out potential confounding influences. In our setting the main concern regarding omitted variables is that the demand shock correlates with unknown contemporaneous improvements in the local business environment, rather than capturing a change in demand. Our estimation strategy takes important steps to alleviate this concern by including county-year and state-year fixed effects which eliminate most plausible sources of unobserved heterogeneity. Thus, to bias our results, any omitted variable(s) would have to coincide with the EPA and differentially affect the corn and soybean industries. We therefore review a series of events that occur throughout our sample period and empirically establish whether they confound our inferences.

6.1 Inputs

An obvious confound could be that corn producers increased other factor inputs rather than adopted stacked-variety seeds to raise yields. The evidence in Table 5 indicates that this was not the case. Specifically, we find no evidence of a significant change in the per acre capital stock, labor or fertilizer inputs within the corn sector post 2005. Moreover, there is no change in the incidence of other productivity-enhancing technologies such as irrigation.

Next, we explore whether the technical change we observe in the data was due to a reduction in the costs of stacked-variety seed. That is, adoption of stacked-varieties is driven by supply-side factors rather than from the demand side as explained by the ethanol boom. The results in column 7 of Table 5 indicate that corn seed costs in fact rose in the post EPA time period relative to the counterfactual although the coefficient estimate is imprecise. The result is unchanged when we use the continuous demand measure in column 8.[21]

[21] One could argue that the main barrier to technology adoption were societal attitudes towards GE technology. For

Table 5: TFP, Input Usage and Technology Costs

Regression no.	1	2	3	4	5	6	7	8
Dependent variable	Land & buildings	Mach & equip	Rented mach	Labor	Fertilizer	Irrigation	SV cost	SV cost
Corn * Post	0.1422	0.0220	0.0981	1.4232	-1.3627	0.0006	0.0495	
	(1.22)	(0.61)	(0.33)	(0.83)	(-0.52)	(0.27)	(1.88)	
Corn * Ethanol capacity								0.0152
								(1.45)
Observations	128	128	128	128	128	14594	126	126
R^2	0.68	0.60	0.40	0.36	0.28	0.97	0.66	0.71
State-year effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
State-industry effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
County-year effects	No	No	No	No	No	Yes	No	No
County-industry effects	No	No	No	No	No	Yes	No	No

Notes: State-level data is used in all regressions except column 6 where county-level data is used. Standard errors are clustered at the state level in all regressions except in column 6 where they are clustered at the county level. t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

6.2 Falsification Tests

As an extension of the idea that there might be alternative explanations for the productivity improvements that we observe we conduct two falsification tests. To do this we leverage the fact that corn is produced in Canada and Texas but producers in these regions did not experience a change in demand after 2005. Given the ethanol industry is concentrated on the Corn Belt we would expect to see productivity increases of similar magnitude in these areas if some spurious industry trend is responsible for the observed productivity increase.

Owing to climatic conditions, Canadian corn and soybean producers are located at more temperate latitudes near the US border and use similar technologies and production methods practiced in the Corn Belt. The operating environment is therefore very similar but Canadian producers were unaffected by the ethanol boom for two reasons. First, the prohibitively high ethanol import tariff levied by the US denied Canadian ethanol manufacturers, and by extension Canadian corn growers, the possibility of exporting ethanol. Second, Canadian producers sell virtually all their output to the domestic feed market. Appendix Table A.2 shows there was no

example, consumers may be hesitant about purchasing food produced using GE seeds. The demand shock may have alleviated this constraint because farmers could use stacked-variety seeds to supply the ethanol industry. This argument is implausible for two reasons. First, stacked-variety seeds contain the same traits (herbicide and pesticide resistance) contained in single-gene corn seeds that are used for food production. Second, by the end of the sample period almost 60% of planted acres used stacked-varieties despite ethanol accounting for 40% of corn sales. It therefore seems that there were general equilibrium effects as the demand shock led to technical change throughout the corn industry, regardless of the eventual use of corn.

increase in Canadian exports or the share of production exported to the US post-2005. Exporting to the US is rare: only 2.3% of Canadian corn is exported and over the sample period this has actually fallen (Table A.2 Panel A). Using data retrieved from the USDA Feed Grains Database, a t-test cannot reject the null that neither the volume of exports nor the share of production exported to the US was affected by the introduction of the EPA (Table A.2 Panel B). Canadian corn producers therefore did not experience a demand shock due to the EPA. Using data on yield per acre for corn and soybean production in nine Canadian provinces obtained from Statistics Canada, we re-estimate equation (13). The results in column 1 of Table 6 show no increase in productivity post 2005.

The ethanol industry is also essentially absent in Texas. Whereas the the average operating capacity of plants within 200 miles of the average Midwestern county is 1086 mgy the requisite figure in Texas is 14.2 mgy. When we use the Texan sample in column 2 of Table 6 the corn-treatment interaction coefficient remains statistically insignificant.[22] The key message from these tests is that productivity only increased in corn-producing areas that were exposed to the demand shock.

6.3 Other Demand Shocks

Clean identification requires that there were no coinciding changes in demand for corn from other sources following implementation of the EPA. We therefore append the estimating equation with interactions between the corn dummy variable and other demand variables and report the results in columns 3 to 5 of Table 6. Despite controlling for differential shocks to export, food and feed demand the Corn-Post coefficient remain positive, statistically significant and comparable in magnitude to the baseline results.

Another potential concern is that the EPA coincides with state-level bans on the use of methyl-tert butyl ether (MTBE) following its discovery in ground water and evidence linking ingestion to carcinogenic diseases. MTBE is a gasoline oxygenate that helps improve motor engine performance and reduces vehicle exhaust emissions. MTBE was originally preferred to ethanol as a gasoline oxygenate because it is less prone to spontaneous combustion. Following the state bans gasoline manufacturers switched from using MTBE to ethanol. The overall effect of this on the level of corn demand was modest, particularly within the Corn Belt where ethanol had historically been the preferred oxygenate (EIA, 2000). Legal challenges to the bans by

[22]These results are not driven by small sample size and the inclusion of a large number of fixed effects. When we estimate less restrictive specifications with just province and year dummies in the model the ATE remains statistically insignificant.

Table 6: Robustness Tests

Regression no.	1	2	3	4	5	6	7	8
Sample	Canada	Texas			Corn Belt			
Corn * Post	19.8491	-3.7643	7.7031***	6.7712***	7.3272***	6.3750***	7.3005***	8.2818***
	(1.27)	(-0.95)	(17.10)	(20.66)	(24.75)	(19.27)	(23.43)	(19.93)
Corn * Exports			-1.4103					
			(-1.52)					
Corn * Feed				1.4385***				
				(5.90)				
Corn * Food					-1.6907			
					(-0.49)			
Corn * MTBE						7.8156***		
						(9.70)		
Corn * Banks							-0.0098	
							(-0.06)	
Corn * Temperature								-0.0098***
								(-11.60)
Corn * Precipitation								3.0079***
								(12.06)
Observations	18,092	18,092	18,092	18,092	18,092	18,092	18,092	18,092
R^2	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.98
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year effect	Yes	Yes s	Yes	Yes	Yes	Yes	Yes	Yes
County-industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the county level and t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

MTBE producers may explain the limited response of ethanol producers. It was only later, in 2006, that MTBE producers were denied liability protection that ethanol became the dominant oxygenate nationwide.

To capture changes in demand for corn arising from the state-level MTBE bans we use information from the Environmental Protection Agency to generate a dummy, MTBE (equals 1 if a state has banned MTBE, 0 otherwise), and interact it with the corn dummy variable. Estimates reported in column 6 of Table 6 show that our main findings are robust to this change. Interestingly, the Corn-MTBE coefficient is positive and statistically significant. Given the MTBE demand shock was due to exogenous health concerns this would have permanently reinforced corn demand. The findings therefore provide further support that increasing demand leads to productivity improvements.

6.4 Additional Robustness Tests

Next, we test the robustness of our findings to differential shocks to finance and climatic conditions. Butler and Cornaggia (2011) provide evidence that access to finance is a key determinant of corn productivity. We therefore interact the corn dummy variable with the number of banks in the county.[23] The main findings reported in column 7 are invariant to this change. Finally, we consider whether climatic shocks drive our key inferences. The results in column 8 of Table 6 show that differential shocks to precipitation and temperature do not confound the effect of demand on productivity.

A further concern is that there were spillover effects on the control group through general equilibrium effects. If so, the ATEs will be spurious due to contamination of the implied counterfactual. To tackle this issue we first use alternative control groups. Column 1 of Appendix Table A.3 reports estimation results that use barley as the control group. Like corn, barley is a major cereal grain that can be used for animal fodder, but like soybeans it cannot be used to produce ethanol. Despite the change in counterfactual, we continue to reach the same conclusion as before. The main results are also unchanged in column 2 of Table A.3 when we use wheat as the control group.

The second procedure we adopt uses Monte Carlo simulations to test whether soybean productivity was directly affected by the EPA. To implement this test we use the county-level soybean productivity data over 2000 to 2010. We randomly assign 50% of counties to placebo treatment status and the rest to control status. The placebo treatment dummy is set equal to

[23]As most firm-bank relationships are local is a good proxy for access to finance

1 for the years 2005 to 2010, and 0 otherwise. We then estimate the equation

$$yield_{it} = \alpha_i + \beta placebo_{it} + \gamma_t + \varepsilon_{it}, \tag{16}$$

and repeat the procedure 1,000 times. As these regressions focus only on observations from the soybean industry, they provide an indication of whether conditional on year effects, soybean yields within the county were significantly higher during the EPA period compared to before. Given that demand for soybeans did not change we would expect the placebo treatment dummy variable to be rejected only by chance. The rejection rates reported in Appendix Table A.4 Panel A are consistent with this view, and indicate no spillover effects. We then repeat the Monte Carlo procedure but use stacked-variety acreage in the soybean industry as the dependent variable to check that the increase in innovation was specific to corn. The rejection rates reported in Panel B of Appendix Table A.4 are again very close to type-1 errors indicating that this was the case.

Next, we investigate whether reallocation of market share explains our findings. In Appendix C we use the procedure outlined by Olley and Pakes (1996) to examine whether reallocation effects are present. The evidence in Appendix Table A.5 rejects the view that reallocation drives our findings. Further evidence in Appendix Table A.6 reinforce this finding.

6.5 Endogeneity of EPA and Ethanol Capacity

Table 7: Lobbying Tests

	Pre-2005	Post-2005	Difference
Corn	0.0400	0.1224	0.0824
Soybeans	0.2800	0.2392	-0.0408
Difference-in-difference			0.1232
			(1.64)

Notes: t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

One could argue that lobbying affected the timing of the EPA. It seems unlikely that atomistic Midwestern corn farmers lobbied politicians and the patterns in contributions to the National Corn Growers Association (the industry lobby) reported in Appendix Figure A.6 are consistent with this view. Likewise, Figure A.7 shows that ethanol producers did not lobby politicians before 2005. In both cases, contributions are low and flat at around \$40,000 per annum between 2002 and 2005 but do increase thereafter. Hence, neither corn nor ethanol producers influenced the timing of the EPA but once in force they were aware of its importance. Figure A.8 also reveals that Monsanto, one of the major seed producers, did not increase lobbying before 2005.

Difference–in-difference estimations reported in Table 7 also produce no evidence of significant differences in lobbying contributions by the treatment and control groups post 2005.[24]

It is clear from Appendix Figure A.9 that ethanol is produced in the same areas in which corn is grown, consistent with the importance of corn as an input in the production of ethanol. An empirical concern is that ethanol location decisions were based on some pre-treatment trend in productivity. For example, the location of ethanol plants could have been chosen because of some positive shock to productivity in the pre-EPA time period, or alternatively that ethanol producers strategically targeted sites that had large productivity gaps relative to the yield frontier.

The agricultural economics literature suggests this was not the case and that the principle determinants of this co-location were shipping costs, the effect that competition from other ethanol plants has on local corn prices, and proximate markets for the sale of DDGs as an animal feed (McAloon et al., 2000).[25] We conduct a similar exercise using our data period, and test the exogeneity of ethanol plant location and capacity expansions with respect to yields within the corn sector. To examine the determinants of entry we estimate the equation

$$y_{ct} = \gamma_c + \beta_1 Yield_{ct} + \beta_2 Output_{ct} + \beta_3 DDG_{ct} + \beta_4 Competitors_{ct} + \gamma_t + \varepsilon_{ct}, \tag{17}$$

where y_{ct} is a 0/1 indicator if at least one ethanol plant enters county c at time t. Similarly, in the capacity expansion regressions y_{ct} is a 0/1 indicator if there is capacity under construction at an existing ethanol plant in county c at time t. $Yield_{ct}$ is the productivity of corn producers in the county; $Output_{ct}$ is the natural logarithm of the number of bushels of corn produced in the county; DDG_{ct} is demand for distillers dry grains proxied by the number of cattle on feed within a 50 mile radius of the countys centroid. DDGs are the principal by-product of ethanol production that can be used as a feedstock for farm animals. They are an important determinant

[24]One could argue that the EPA was undertaken with the goal of raising productivity within the corn sector and that our results will be biased as a result. This does not appear plausible for three reasons. First, there is not a single mention of the word corn in the EPA documents. Second , in unreported Cox Proportional Hazard models we find no significant effect of corn yield on time to enactment (failure) during the years 2000 to 2005. That is, corn yields do not predict the signing into law of the EPA. This result holds when we expand the sample to include earlier years as well.

[25]Using data for ethanol plant entry for 2,979 counties over the period 1995 to 2005 Sarmiento et al. (2012) provide evidence that the probability of a new ethanol plant locating in a county is significantly lower if that county lies within a 30 mile radius of an existing ethanol plant. By 60 miles this distance effect is close to zero. They infer from this a strong desire to avoid competition in procurement of corn. A consequence is that most US counties contain one or no ethanol plants. This is consistent with evidence from McNew and Griffiths (2005) who show that the opening of an ethanol plant significantly increases corn prices only within 150 miles of the plant and Fatal and Thurman (2012) who find that local price effects diminish to zero as the distance between the county and ethanol plant reaches 103 miles.

Table 8: Exogeneity Tests

Regression no.	1	2	3	4	5	6	7	8	9	10
			Entry					Capacity under construction		
Yield	-0.0000	-0.0003	-0.0002	-0.0003	-0.0003	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.18)	(-1.44)	(-1.22)	(-1.59)	(-1.52)	(-0.45)	(-0.99)	(-1.10)	(-0.70)	(-0.70)
Output		0.0243	0.0191	0.0211	0.0170		0.0107	0.0119	0.0050	0.0051
		(1.61)	(1.25)	(1.40)	(1.14)		(1.36)	(1.53)	(0.63)	(0.65)
DDGs demand		1.4428**	1.5728**	1.5149**	1.6033**		0.8603*	0.8391*	1.0306**	1.0296**
		(1.97)	(2.20)	(2.09)	(2.28)		(1.75)	(1.76)	(1.98)	(1.99)
Plants within 100 miles		-0.0052***					0.0037***			
		(-4.46)					(2.60)			
Plants within 200 miles			-0.0028***					0.0015***		
			(-5.19)					(2.60)		
Capacity within 100 miles				-0.0001***					0.0000	
				(-6.01)					(0.33)	
Capacity within 200 miles					-0.0000***					0.0000
					(-6.81)					(0.39)
Observations	8,276	8,209	8,209	8,209	8,209	8,276	8,209	8,209	8,209	8,209
R^2	0.74	0.74	0.74	0.74	0.74	0.27	0.27	0.27	0.27	0.27
County effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Entry is a dummy variable equal to 1 if at least one ethanol plant enters county c at time t, 0 otherwise. Capacity under construction is a dummy variable equal to 1 if there is any ethanol capacity currently being installed in county c during year t, 0 otherwise. The sample excludes the years 2000 and 2001 because *The Ethanol Industry Outlook* does not provide data before 2002. The standard errors are clustered at the county level and the associated t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

of ethanol producers profitability, accounting for between 15% and 20% of revenues (Hofstrand, 2013; McAloon et al., 2000; Sarmiento et al., 2012; USDE, 2013). Building on current evidence we construct two measures of $Competitors_{ct}$. First, the number of other ethanol firms located within a 100 (or 200) mile radius of the county; and second, ethanol operating capacity within a 100 (or 200) mile radius of the county. These distances are chosen as conservative estimates of the radius in which other ethanol plants are likely to have an effect on the location of new ethanol plants found elsewhere in the literature. A full set of county γ_c and year γ_t dummies are also included in the model. ε_{ct} is the error term. We estimate equation (17) using a linear probability model due to the inconsistency of fixed-effect probit models.

The results of these tests are provided in Table 8. There are three key findings, all of which are similar to evidence already found in the literature. First, the behavior of ethanol plants is orthogonal to our measure of productivity within the corn sector, yield. This is consistent with the view that we do not somehow capture pre-treatment differences in the productivity of corn when using the ethanol capacity variable. Instead, strategic profitability motives appear to drive location decisions. Consistent with evidence for older plants, entrants are significantly more likely to locate in a county that is away from existing ethanol plants, or areas with low levels of installed ethanol capacity. Entry is also more likely in counties near to DDGs markets.

In regressions 6 to 10 of the table we repeat the exercise but investigate the determinants of capacity expansions. Again, we fail to find corn productivity or output were determinants of capacity expansion choices. Rather there is evidence of a positive link between DDGs demand and capacity under construction. The size and location of ethanol plants appear therefore, to be unrelated to productivity in the corn sector.

7 Conclusions

This paper develops a theory in which demand shocks trigger technical change and productivity improvements. We test the theoretical predictions by exploiting a natural experiment in the US corn industry where market demand exogenously increased following modifications to energy policy which triggered a sharp increase in ethanol production. Using difference-in-difference estimations that leverage the fact that soybeans are grown in close proximity to corn but cannot be used to manufacture ethanol we find robust evidence that demand causes firms to improve the technologies they use and improve productivity. Economically, we find that productivity increased by approximately 5.7% per annum within the treatment group as producers adopted a new seed technology.

The model suggests that demand shocks affect productivity through two channels. Larger market size generates a direct effect on the incentives to innovate, and an indirect effect through product market competition which further stimulates innovation. We find evidence of both effects although the former is considerably larger in magnitude. A host of robustness and falsification tests rule out a number of potential confounds.

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Supplementary Appendix

Apprendix A

Firm problem

The current value Hamiltonian for the firm problem is:

$$\begin{aligned}\mathcal{H}_t &= \Big[(p_t - \tilde{z}_t^{-\eta})q_t - h_t - \lambda\Big] + v_t A k_t h_t \\ &= \left[\left(\frac{E_t}{X_t^{\alpha}}\ (\hat{x}_t + q_t)^{\alpha-1} - \tilde{z}_t^{-\eta}\right) q_t - h_t - \lambda\right] + v_t A k_t h_t,\end{aligned}$$

where v_t is the costate variable. The first order conditions for the problem above, under symmetry, are

$$\frac{\partial \mathcal{H}_t}{\partial q} = 0: \quad \tilde{z}_t^{-\eta} = \theta \underbrace{\frac{E}{X_t^{\alpha}} x_t^{\alpha-1}}_{p_t} \tag{18}$$

$$\frac{\partial \mathcal{H}_t}{\partial h} = 0: \quad v_t A k_t = 1 \tag{19}$$

$$\frac{\partial \mathcal{H}_t}{\partial\ \tilde{z}} = \eta \tilde{z}^{-\eta-1} q_t = -\dot{v}_t + \rho v_t. \tag{20}$$

From (18), firms charge a markup over marginal costs, with $\theta \equiv (n-1+\alpha)/n$ being the inverse of the markup. This is the well-known result in Cournot-type equilibria that the markup depends on the perceived demand elasticity, which is a function of both the demand elasticity and the number of competitors.[26]

Equation **(9)**. Rearranging (18), we obtain $x_t = \tilde{z}_t^{\eta \frac{1}{1-\alpha}} (\theta E / X_t^{\alpha})^{\frac{1}{1-\alpha}}$. Substituting it into (1) yields

$$X_t^{\alpha} = \left(\int_0^1 \tilde{z}_{jt}^{\hat{\eta}}\ \mathrm{d}j\right)^{1-\alpha} (\theta E)^{\alpha},$$

[26] It can be easily shown that condition (18) is the solution of the corresponding static Cournot game with given productivities. Consistently with Cellini and Lambertini (2005), the solution to the open loop equilibrium coincides with the closed loop when $\hat{\eta} = 1$, since in this case the externality k in the FOC (19) does not depend on the productivity of direct competitors.

where $\hat{\eta} \equiv \eta\alpha/(1-\alpha)$. Using this into the expression for x above, we find

$$x_t^{\alpha} = (\theta E)^{\alpha}\, \tilde{z}_t^{\hat{\eta}} \left(\int_0^1 \tilde{z}_{jt}^{\hat{\eta}} \,\mathrm{d}j \right)^{-\alpha}.$$

Substituting these expressions for x and X into (18), considering that in a symmetric equilibrium $x = nq$ we obtain (9).

The stationary growth rate (10) is obtained differentiating (19) with respect to time, which yields $-\dot{v}/v = \dot{k}/k = \dot{\tilde{z}}/\tilde{z}$. Plugging it, (9), and (19) into (20), we obtain (10).

Free entry: proofs

Using (MC) and (FE) to substitute away e we obtain

$$\frac{\frac{1}{n} + \frac{\rho}{A}}{\beta + (1+\eta)\theta} = \frac{\rho\phi - \frac{\rho}{A}}{1 - (1+\eta)\theta}, \tag{21}$$

since θ is increasing in n, the left-hand-side (LHS) is decreasing in n and the right-hand-side is increasing in n. At the minimum possibile value of n, $n = 1$, the inverse of the markup $\theta = \alpha$, and under the following parameter condition

$$\frac{1 + \frac{\rho}{A}}{\beta + (1+\eta)\alpha} > \frac{\rho\phi - \frac{\rho}{A}}{1 - (1+\eta)\alpha}$$

an equilibrium number of firms exists and is unique.

An increase in the demand for the differentiated good sector, a reduction in β, shifts the LHS of (21) to the right, while not affecting the RHS, and ultimately leads to a higher equilibrium number of firms n. The free entry condition (FE) shows that a higher n implies higher expenditure per firm e. Using these results into (11) and (10) allow us to prove the growth effects of the demand shock.

Appendix B: Variable Definitions

Yield is the number of bushels produced per acre in industry i in county c during year t.

TFPQ is physical TFPQ in industry i in state s during year t calculated using equation (12).

Ethanol capacity is the operating capacity (in logarithms) of ethanol plants within a 200 mile radius of county c during year t. Because The Ethanol Industry Outlook provides data on ethanol plants from 2002 onward, we use the 2002 values for 2000 and 2001.

Firms is number of firms (in thousands) operating in industry i in county c during year t.

EPA is a dummy variable equal to 1 for the years 2005 to 2010 if an observation is from the corn industry, 0 otherwise.

Acres planted is number of acres planted in industry i in county c during year t.

Irrigation is the ratio of acres irrigated to total acres planted in industry i in county c during year t.

GE share is the ratio of acres planted using stacked-variety seed to total acres planted in industry i in county s during year t.

Irrigation is the ratio of acres irrigated to total acres planted in industry i in county c during year t.

Land & buildings is the per acre value of land and buildings (in thousands of $) in industry i in state s during year t.

Machinery & equipment is the per acre value of machinery and equipment (in thousands of $) in industry i in state s during year t.

Rented machinery is the per acre value of rented machinery (in thousands of $) in industry i in state s during year t.

Labor is the per acre number of labor hours in industry i in state s during year t.

Fertilizer is the per acre value of fertilizer used in industry i in state s during year t.

GE cost is the per acre cost of stacked-variety seed (in thousands of $) used in industry i in state s during year t.

Exports is the value of exports (in logarithms) in industry i during year t.

Feed is the value of animal feed sales (in logarithms) in industry i during year t.

Food is the value of sales to the food sector (in logarithms) in industry i during year t.

MTBE is a dummy variable equal to 1 if state s has banned the use of MTBE during year t, 0 otherwise.

Banks is the number of banks operating in county c during year t.

Temperature is the average number growing degree days (in thousands) over the growing season in county c during year t.

Precipitation is the average number of millimetres of rainfall per day over the growing season in county c during year t.

Output is the number of bushels produced in industry i in county c during year t.

DDGs demand is proxied using the number of cattle on feed in the county (in millions) in county c during year t.

Plants within 100 (200) miles is the number of ethanol plants within a 100 (200) mile radius of the centroid of county c during year t.

Capacity within 100 (200) miles is the capacity of ethanol plants within a 100 (200) mile radius of the centroid of county c during year t.

Entry is a dummy variable equal to 1 if an ethanol plant enters county c during year t.

Capacity under construction is a dummy variable equal to 1 if ethanol plant capacity is under construction in county c during year t.

Appendix C: Tables

Table A.1 reports the real annual per acre cost of single-gene and stacked-variety seeds. All variables are deflated into 1992 US dollars using the NASS Seed Price Index. Data on seed price per acre are taken from the NASS reported in the "Seed Premium-Farm Income Database" held by The Organic Center.

Table A.1: Seed Cost per Acre

Year	Single-Gene	Stacked-Variety
2001	27.83	35.88
2002	28.80	37.94
2003	32.90	41.63
2004	37.70	50.48
2005	38.82	54.45
2006	40.37	58.14
2007	50.14	77.22
2008	64.26	102.81
2009	69.42	117.36
2010	83.54	147.66

Canadian Falsification Test

Table A.2: Canadian Corn Production and Exports to the US

Panel A: Descriptive Statistics					
Year	Production	Yield	Exports to US	Export Share (%)	
2000	6,954	119	297	4.27	
2001	8,389	111	111	1.32	
2002	8,999	117	194	2.16	
2003	9,587	120	297	3.10	
2004	8,837	114	294	3.33	
2005	9,332	124	203	2.18	
2006	8,990	138	108	1.20	
2007	11,649	142	117	1.00	
2008	10,643	141	360	3.38	
2009	9,796	139	226	2.31	
2010	12,043	133	124	1.03	
Panel B: t-tests					
		Pre-2005	Post-2005	Diff	t-stat
Exports		238.60	189.67	49.93	0.89
		(37.52)	(39.49)	(55.25)	
Export share		2.83	1.85	0.98	1.58
		(0.51)	(0.39)	(0.63)	

Notes: Production and exports to the US are measured in 1,000 metric tons. Yield is measured in bushels per acre. Export Share is the percentage of production that is exported to the US Production data are taken from Statistics Canada and export data are taken from the USDA Feed Grains Database Table 24. Panel B reports t-tests on the null of equality between exports and export shares during the pre- (2000 to 2004) and post-EPA (2005 to 2010) periods.

Panel A in Table A.2 reports summary statistics on the Canadian corn sector. Exports to US is the total tons of corn (in 1,000 metric tons) exported to the US, taken from the USDA Food Grains Database. Export share is the ratio of exports to the US divided by production. In Panel B we report the results of t-tests that examine whether the volume of exports, or the share of corn production exported to the US changed following implementation of the EPA. In both cases we find that these values actually decreased, but there are no statistically significant differences between periods. Combined with the persistently low incidence of exporting by Canadian corn producers, we conclude that there was no increase in demand for corn in Canada because of the demand shock in the US.

Spillover Effects

1. Alternative Control Groups

Table A.3: Alternative Contols

Regression no.	1	2
Control group	Barley	Wheat
Corn * Post	11.3283***	8.5056***
	(7.95)	(15.72)
Observations	3,379	10,351
R^2	0.90	0.95
County-year effect	Yes	Yes
County-industry effects	Yes	Yes

Notes: The number of observations is lower compared to the baseline estimates because there are fewer counties which grow both corn and barley/wheat during the same year. Standard errors are clustered at the county level and t-statistics are reported in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels.

2. Monte Carlo Simulations

Table A.4: Monte Carlo Placebo Tests

Panel A: Placebo Test Soybean Yield (Spillover Test)	Panel B: Placebo Test Soybeans GE Acreage Share
Number of replications: 1,000	Number of replications: 1,000
Rejection rate at the 1% level (2-tailed test): 1.3%	Rejection rate at the 1% level (2-tailed test): 2.7%
Rejection rate at the 5% level (2-tailed test): 5.1 %	Rejection rate at the 5% level (2-tailed test): 6.8%
Rejection rate at the 10% level (2-tailed test): 10.8%	Rejection rate at the 10% level (2-tailed test): 9.9%

Notes: The table reports results of placebo tests. In both panels the estimating equation is $yield_{ct} = \alpha_c + \beta Placebo_{ct} + \gamma_t + \varepsilon_{ct}$. The placebo treatment is randomly assigned to approximately 50% of observations in the soybean sector. In both panels the sample spans the years 2000 to 2010. County-level data is used in Panel A; state-level data is used in Panel B. The standard errors are clustered at the county level in Panels A; at the state-level in Panel B. The rejection rate is the percentage of t-statistics that exceed the critical value at the 10%, 5%, and 1% levels, and denote the percentage of times the null hypothesis, that β is equal to zero in the above equation, is rejected.

Reallocation and Selection Effects

Our findings indicate a robust increase in productivity and innovation within the corn sector and suggest this stems from within-firm productivity improvements. However, reallocations of market share may also explain the results (Asplund and Nocke, 2006).

The county-industry structure of our data render it impossible to apply a productivity decomposition such as that in Foster et al. (2001) to judge the relative importance of the within-firm, between-firm, entry and exit channels to industry productivity growth. However, Olley and Pakes (1996) outline a productivity decomposition that eschews following firms over time and instead decomposes the aggregate productivity level using

$$p_t = \bar{p}_t + \Sigma_i \Delta s_{it} \Delta p_{it} \tag{22}$$

$$= \bar{p}_t + cov(s_{it}, p_{it}), \tag{23}$$

where $\Delta s_{it} = s_{it} - \bar{s}_{it}$ and $\Delta p_{it} = p_{it} - \bar{p}_{it}$. $p_t = \Sigma s_{it} p_{it}$ is industry productivity at time t; s_{it} is county i's output market share at t; p_{it} is county i's productivity; $\bar{p}_t$ and $\bar{s}_t$ represent unweighted mean productivity and market share, respectively.

This procedure decomposes industry productivity into a component capturing shifts in the productivity distribution ($\bar{p}_t$) and another component capturing market share reallocations via the change in the covariance component. The higher the covariance, the higher the share of output that goes to more productive counties. We first inspect the relative importance of the two components using the county-level yield data to measure productivity. In Panel A of Appendix Table A.5 we find that reallocation of market share accounts for less than 20% of aggregate industry productivity in all years. The decomposition of industry productivity also provides no evidence of a sharp jump in the county-level covariance after the EPA. In fact, the reverse appears to be true and reallocations of market share become less important post 2005. We formally test this by retrieving the annual covariance value for the corn and soybean industries and use it as the dependent variable in equation (13). In Panel B of Table A.4 the Corn-Post interaction is statistically insignificant. The contribution of reallocations of market share to overall corn industry productivity was therefore similar between the pre- and post-treatment periods. In the remainder of the table we repeat the analysis using TFPQ and TFPR to measure productivity. The data more strongly refute the view that reallocation of market share explains our main results.[27]

[27]This conclusion is unchanged when we use acres planted to measure market share.

Table A.5: Productivity Decomposition

Panel A: [?] Productivity Decomposition									
Productivity measure		Yield			TFPQ			TFPR	
2002	1.0000	0.8125	0.1875	1.0000	0.9936	0.0064	1.0000	0.9970	0.0030
2003	1.0624	0.8919	0.1704	1.4543	1.4535	0.0008	1.3485	1.3480	0.0005
2004	1.1840	1.0335	0.1506	1.5097	1.5094	0.0003	1.3248	1.3246	0.0002
2005	1.1013	0.9562	0.1451	1.4819	1.4811	0.0008	1.3028	1.3025	0.0004
2006	1.1075	0.9582	0.1493	1.4744	1.4739	0.0005	1.4003	1.4000	0.0003
2007	1.1218	0.9782	0.1436	1.4792	1.4788	0.0004	1.4410	1.4407	0.0003
2008	1.1488	1.0172	0.1318	1.5320	1.5317	0.0003	1.4529	1.4527	0.0001
2009	1.2155	1.1117	0.1037	1.5094	1.5093	0.0001	1.4343	1.4342	0.0001
2010	1.1310	1.0146	0.1163	1.4841	1.4836	0.0005	1.4888	1.4885	0.0003

Panel B: Covariance difference-in-difference results		
Dependent variable: $\Sigma \Delta s_{it} \Delta p_{it}$	Yield	TFPQ
Corn	0.0802***	-0.0009
	(3.22)	(-0.65)
Corn * Post	-0.0217	-0.0001
	(-0.86)	(-0.07)
Observations	18	18
R2	0.96	0.92
Year effects	Yes	Yes

Notes: Panel A reports the individual components of the Olley and Pakes (1996) productivity decomposition. Panel B reports difference-in-difference estimates of equation (13) using the annual covariance term as the dependent variable. Standard errors are clustered at the year level and the corresponding t-statistics are reported in parentheses.

Table A.6: Reallocation of Market Share

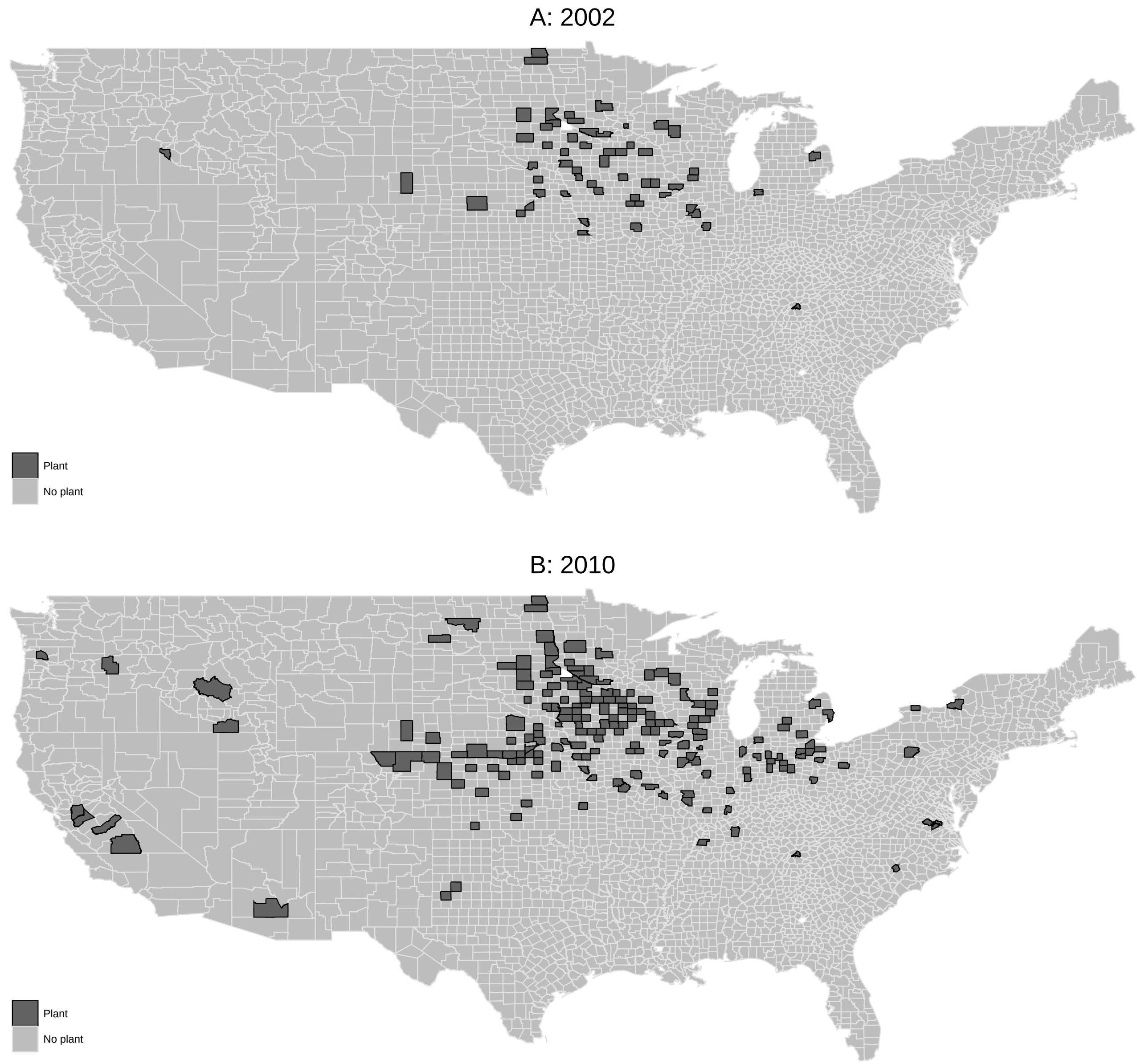
Pre-treatment productivity quartile	1st		2nd		3rd		4th	
Period	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Yield	85	103	120	134	140	151	167	171
Share of acres (%)	9	10	16	16	27	27	47	47
Share of output (%)	5	6	13	14	26	26	56	54

Notes: Pre-treatment productivity quartile indicates the quartile of the yield distribution during the years 2000 to 2004. "Pre" represents the years 2000 to 2004 whereas "Post" denotes the years 2005 to 2010. Share of acres (%) is the quartile's share of industry acres planted. Share of output (%) is the quartile's share of industry output.

Our second approach to investigate reallocation effects is to examine counties' market shares. Under the assumption that there is no within-firm productivity change over the sample period, all of the productivity gains must be driven by reallocation of market share from low- to high-productivity counties. If reallocation effects are present, we should be able to document an increasing concentration of economic activity among the most productive counties. We address this issue by splitting the counties into quartiles based on their pre-2005 productivity. Next, we compare how market share (captured by the share of acres and output) evolves within each quartile through time. Appendix Table A.6 shows no evidence that market share became more concentrated within the most ex ante productive counties. Each quartile's market share remains broadly constant across time which suggests that the ATEs we found previously do not reflect reallocation.

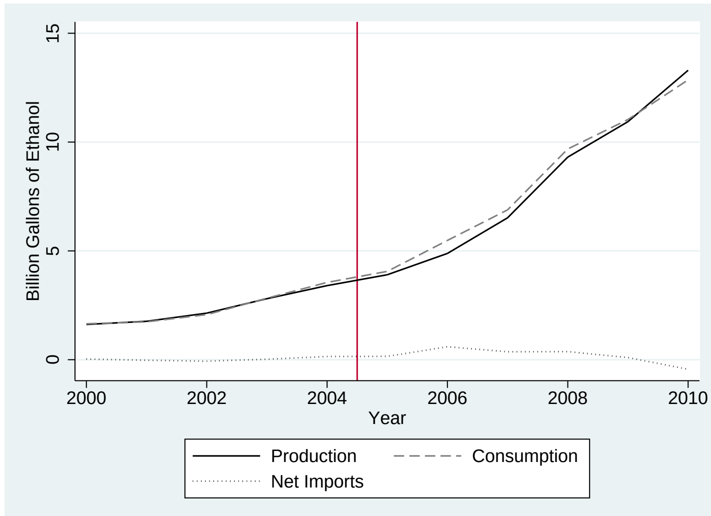
Appendix D: Figures

Figure A.1: Ethanol Plant Location



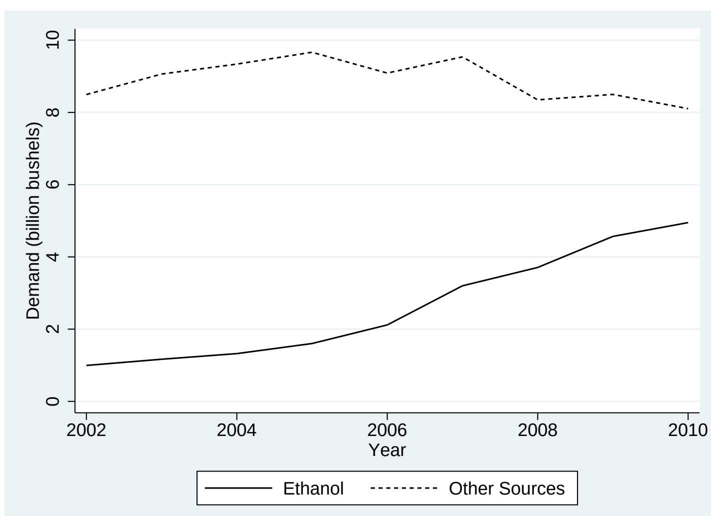
Notes: This figure plots the location of ethanol plants in the continental US for the years 2002 (Panel A) and 2010 (Panel B). Only ethanol plants that use corn as their feedstock are shown.

Figure A.2: Ethanol Production, Consumption and Imports



Notes: This figure reports the number of gallons of ethanol produced, consumed and imported by the US. Data are taken from the 2011 EIA Annual Energy Review, Table 10.3.

Figure A.3: Sources of Corn Demand



Notes: This figure plots the annual number of bushels of corn purchased for use in the ethanol industry and by other sectors (exports, feed, food and seed) between 2002 and 2010. The data are taken from the USDA Economic Feed Grains Database, Table 2.

Figure A.4: Productivity Evolution Controlling for Time Effects

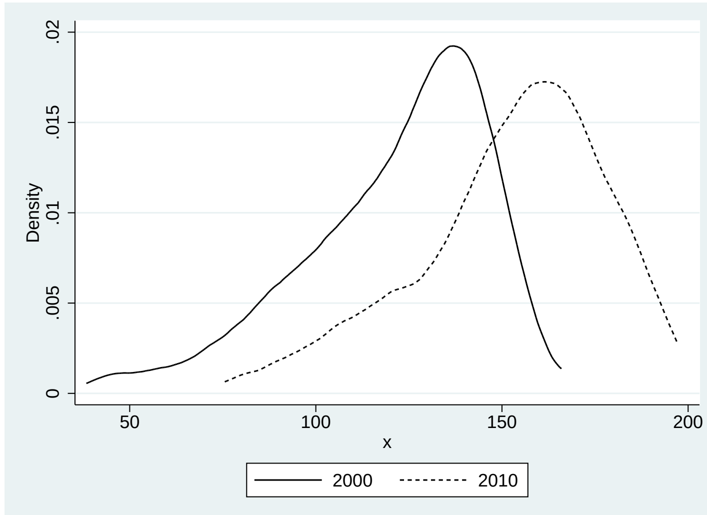
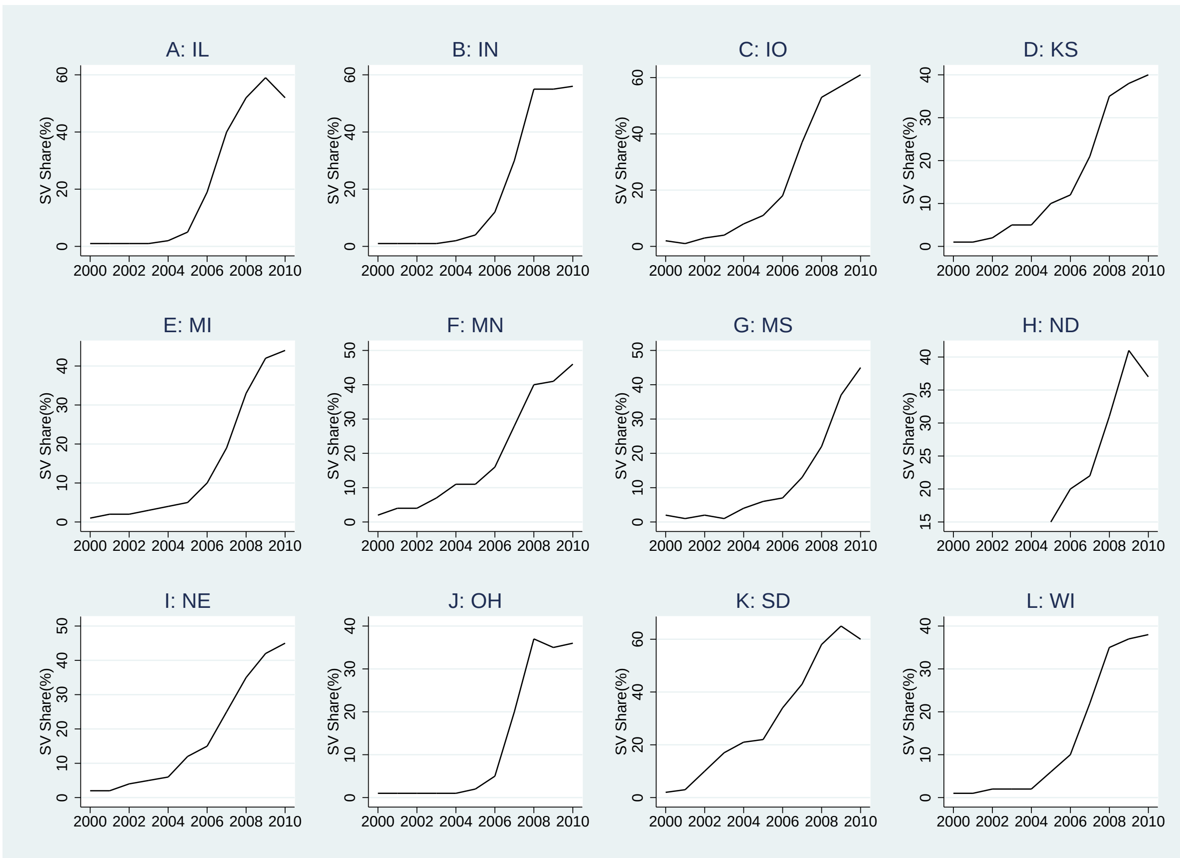


Figure A.4 reports the distribution of corn yield in 2000 and 2010 taking into account year effects. Specifically, we estimate the equation

$$yield_{it} = \alpha + \gamma_t + \varepsilon_{it} \tag{24}$$

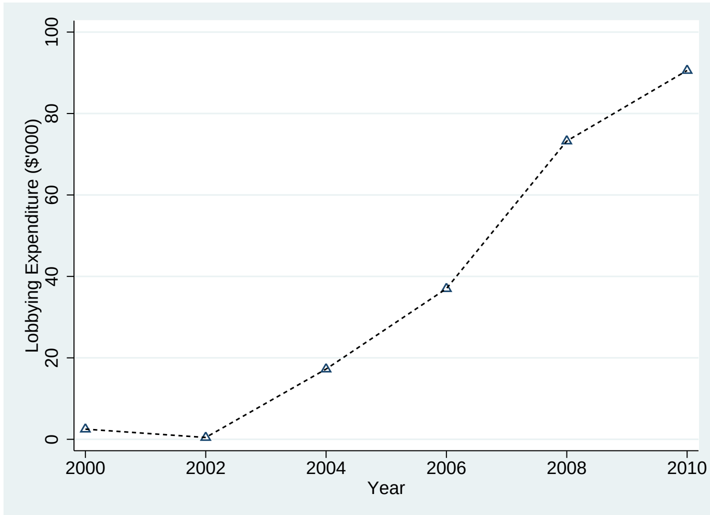
where γ_t represent year fixed effects. We then use the residuals from this regression to plot Figure A.4.

Figure A.5 Stacked Variety Share of Acres



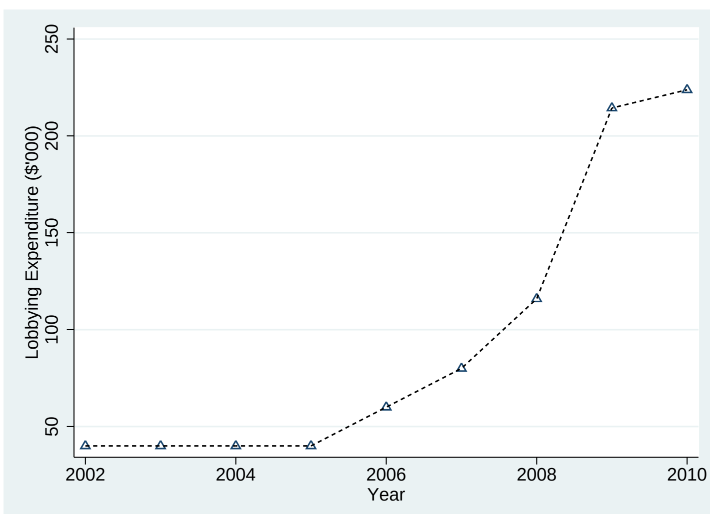
Notes: This figure plots the annual percentage of corn acres planted using stacked-variety seeds in each state within our sample. Years are plotted on the x-axis in all panels and the percentage of acres planted using stacked-variety seeds is on the y-axis. The labels above each panel indicate which state the data relate to.

Figure A.6: National Corn Growers Association Contributions



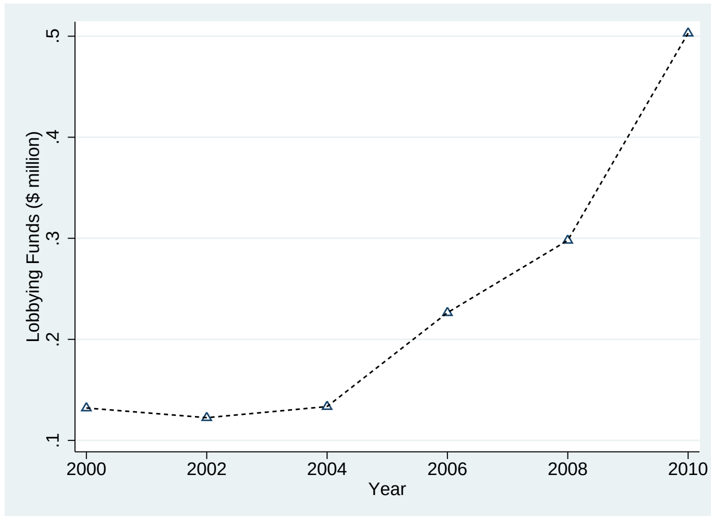
Notes: This figure plots annual contributions to the National Corn Growers Association during the sample period. All data are taken from http://www.opensecrets.org.

Figure A.7: Ethanol Lobbying Expenditure



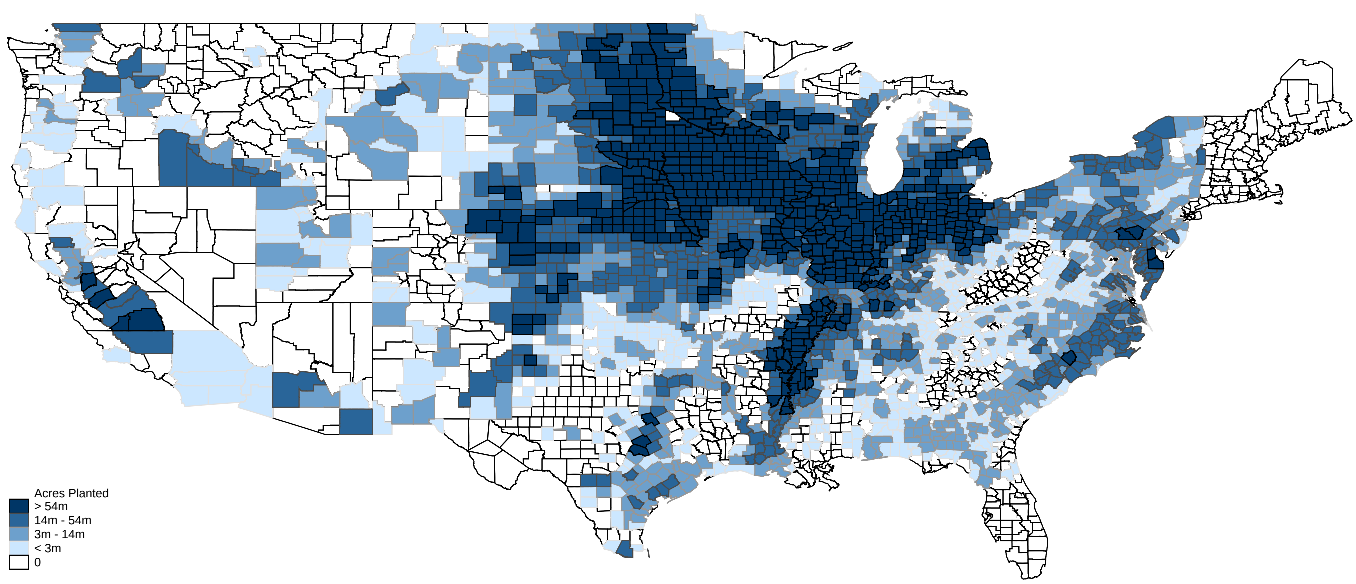
Notes: This figure plots annual lobbying expenditure by the American Coalition for Ethanol during the sample period. All data are taken from http://www.opensecrets.org. No lobbying contributions are reported before 2002.

Figure A.8: Monsanto Lobbying Expenditure



Notes: This figure plots annual lobbying expenditure by Monsanto Corporation during the sample period. All data are taken from http://www.opensecrets.org.

Figure A.9: Average Planted Acres of Corn 2000-2010



Notes: This figure plots the average annual number of planted corn acres of corn in each county during the sample period 2000 to 2010.