



## DEMAND-DRIVEN TECHNICAL CHANGE AND PRODUCTIVITY GROWTH: THEORY AND EVIDENCE FROM THE ENERGY POLICY ACT\*

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We present novel evidence on the effect of market size on technology adoption and productivity. Our tests exploit a natural experiment in the U.S. corn industry where changes to national energy policy created exogenous increases in demand. Difference-in-difference estimates show that the demand shock caused technical change as corn producers adopted higher quality seeds which in turn raised productivity by 7%. We develop a simple model that formalizes the mechanisms underlying our results.

### I. 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 decision to introduce or adopt new technologies.

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In this paper, we present novel evidence that demand shocks provoke productivity improvements by inducing technology adoption. Much of our understanding about the relationship between market size and productivity comes from the pharmaceutical industry (Acemoglu and Linn [2004]; Dubois *et al.* [2015]; Blume-Kohout and Sood [2013]). These studies find that market size promotes innovation, although with differently sized elasticities. The evidence presented in this paper supports this work, albeit for an industry where innovation is quite different. Innovation within the pharmaceutical sector is characterized by very expensive and very long innovation cycles, protected by strict legal protections. However, firms in many sectors of the economy rely on innovations by outside firms. The evidence we provide is for the adoption of an existing technology. Technology adoptions of this type are arguably, more likely to be prevalent in the wider economy, and responsive to smaller aggregate demand shocks.

Our tests revolve around a natural experiment in the U.S. corn industry. The Energy Policy Act of 2005 (EP Act) mandated an increase in the ethanol content of gasoline which sparked a wave of ethanol plant openings that raised demand for corn, the key intermediate input in ethanol production. The driving force behind the legislation was fear among national policymakers that the U.S. economy was vulnerable to interruption of overseas energy supplies. The EP Act sought to improve energy independence and security through an array of measures including increased use of ethanol in gasoline (Diggs [2012]). Neither productivity nor technological considerations within the corn industry motivated the EP Act and there is no evidence of lobbying activity preceding the legislation, by either corn or seed producers.<sup>1</sup> To establish causality we exploit the fact that the EP Act had no effect on demand for wheat which is produced in the same locations as corn, uses similar production processes but is not used to manufacture ethanol.

Given our focus on established producers, we use difference-in-difference estimations that compare the evolution of physical productivity measures within the corn industry with wheat productivity in the same Midwestern county. We use crop yields (the number of bushels produced per acre), the standard 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.<sup>2</sup> 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

<sup>1</sup> 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. We are able to show 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].

<sup>2</sup> 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.

that may make firms appear more productive even if underlying technical efficiency is unchanged. Rather, we exclusively study how the changes in 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 average treatment effect (ATE) equates to a 7% increase in yield per acre. In addition, we find a statistically significant 0.8% increase in TFPQ, indicating that the productivity gains do not simply capture adjustments to input usage. In fact, further tests show that the demand shock had no effect on the per acre quantity of capital, labor, fertilizer, seed or other intermediate inputs.<sup>3</sup>

Subsequent tests show that the productivity improvements are driven by technology adoption. Following the demand shock, corn producers rapidly adopted a new seed, stacked-variety corn seeds (SV seeds henceforth), that had been commercially available for several years but were seldom used. These represented an upgrading in the quality of inputs because they blend existing pest tolerance (Bt) and herbicide tolerance (Ht) genes into a single variety. Stacked-variety seeds produce more bushels per acre relative to single-gene (Bt or Ht) seed types by allowing the crop to get closer to its yield potential. However, farmers incur fixed costs when adopting SV seeds due to search costs, changes in production methods, and learning how to use different machinery (Vyn [2010], Fernandez-Cornejo *et al.* [2018]).

We find the adoption of SV seeds caused a significant increase in productivity within the corn industry. A 10% increase in the SV technology leads to a 0.7% productivity gain. By the end of the sample period SV seeds account for approximately 50% of planted acres, indicating they account for the majority of the observed productivity gains. Our findings on the link between the adoption of new seeds and productivity growth echo the results in Bustos *et al.* [2016], who study the introduction of genetically engineered seeds in Brazil which raised labor productivity.

Technology adoption and productivity improvements could derive from supply-side forces. For example, if the cost of SV seeds falls through time producers may adopt the more productive technology irrespective of demand conditions. The data decisively refute this view. First, there is no reduction in the per acre cost of SV seed during the sample period. Rather, stacked-variety seeds are more costly compared to single-gene seeds and this relative price difference actually grew through time. Second, falsification tests show no evidence of significant productivity increases among Texan corn producers that were unaffected by the ethanol demand shock. Operating practices, seed availability and seed prices are similar in the Corn Belt and Texas. However, their location far from ethanol plants and the high associated transport costs

<sup>3</sup> Evidence from the agricultural literature suggests that these additional TFP effects arose because of other complementary changes to farming practices, in particular to tillage.

meant that the ethanol boom did not affect demand for 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 and spillover effects on the control group. We explore these alternative mechanisms but find little support for them in the data. Moreover, our estimations include county-year fixed effects which rule out time-varying productivity and technological shocks common to both groups at the local and macro levels. This approach has the attractive property that the ATE is identified through comparisons of the treatment and control group within the same county-year.

We construct a simple model to provide a framework to interpret these results. An industry is composed of firms that are heterogeneous in productivity producing varieties of the same product. Since the adoption of SV seeds leads to a reduction in labor per unit of output, following Bustos *et al.* [2016] we characterize it as a labor-augmenting technical change. Each firm has the option to operate with its current technology or pay a fixed cost to adopt a superior, more productive technology. Due to the adoption cost, only a few highly productive firms can pay it and upgrade to the new technology. A larger market size leads to a higher share of firms adopting the more efficient technology. Hence, demand pull shocks generate increases in firms' revenues which stimulates technology adoption and productivity growth.

Our research is important for three reasons. The corn industry accounts for a large share of U.S. agricultural employment and approximately 30% of agricultural output. Understanding the drivers of corn productivity dynamics therefore matters for the agricultural sector. Moreover, evidence from this industry is likely to generalize to other settings. Corn producers rely on off-the-shelf technologies created by external firms. This is similar to the situation in many industries where R&D expenditure is concentrated within a select few companies. Our laboratory also allows us to exclusively study the effects of demand on productivity and shutdown the confounding competition channel that is present in studies assessing the effects of market size due to trade liberalization.

### I(i). *Literature Review*

Our paper is related to several strands of literature. Market size is often viewed as an important determinant of productivity-enhancing investments such as innovation and technology adoption. Increases in actual or potential market size generate profit incentives that pull firms into 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]).

The link between market size, technological change and productivity has also been at the center of the recent literature on trade and firm heterogeneity. Our model contains insights from Yeaple [2005] and Bustos [2011], where heterogeneous firms select into technology upgrading following increases in market size brought about by trade liberalization. Recent models of trade and innovation embed both extensive and intensive margins of productivity growth in response to larger market size (Dhingra [2012], Impullitti and Licandro [2017], and Impullitti *et al.* [2017]).

Early studies by Schmookler [1954] and Griliches [1957] identified market size effects as a key force behind new inventions and technology adoption. Similarly, Jaffe [1988] and Cohen and Klepper [1996] find a positive link between firm size and R&D intensity. In his summary of the available empirical evidence, Cohen [2010] argues that demand-pull theories do not typically survive empirical scrutiny however, in part because they often ignore important industry characteristics, use imperfect proxies for demand and lack compelling strategies to deal with issues of endogeneity.

A large empirical macro and trade literature studies the effects of market size on technological change. Owing to difficulties in establishing causality in macro settings, a more common approach in recent years has been to use micro data and specific policy induced liberalization events. For example, Bustos [2011] shows that the introduction of 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. Lileeva and Treffer [2010] show that Canadian firms which experienced an increase in market size following the Canada-U.S. Free Trade Agreement raised their labor productivity by investing in innovation and adopting new technologies. Griffith *et al.* [2010] find that the EU Single Market Programme (SMP), which deregulated the product market, is associated with increased product market competition and with increases in innovation and productivity growth. While these papers emphasize the importance of increased market potential in driving this change, trade liberalization typically occurs simultaneously with changes in competition. This point is made by Aghion *et al.* [2017] who analyze the effects of demand shocks generated by exports on French firms' innovation decisions. They find evidence of a market size effect of exports on innovation, which can be offset by increased competition on innovation effort. In our setting, tariffs on ethanol are high and do not change, acting as a barrier to import competition. In addition, in an industry characterized by

a few large firms with high sunk costs, such as corn, the entry margin is not likely to be strong and we should not expect large pro-competitive effects of changes in demand. This allows for a better identification of the market size effects of a demand shock.

The paper is organized as follows. In the next section we outline a theoretical model to help interpret the empirical results. We describe the data set in Section III. Section IV 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 V. Section VI contains an exhaustive set of robustness tests. Conclusions are drawn in Section VII.

## II. A SIMPLE MODEL

We devise a simple model of technology adoption to highlight some key economic mechanisms which help interpret our empirical findings. As we detail below, there exists a high degree of heterogeneity in size and productivity across corn producers in different counties. We therefore outline a model in which firms differ along these margins.<sup>4</sup>

### II(i). *Economic Environment*

Corn is produced in many substitutable varieties by a continuum of monopolistically competitive firms.<sup>5</sup> Each variety  $j$  is produced by a firm with a productivity  $\tilde{z}$  drawn from a Pareto distribution  $F(\tilde{z})$  with shape  $k$  and location  $\tilde{z}_{\min}$ .<sup>6</sup> After observing productivity, firms decide whether or not to enter and produce. After entering, firms can produce output with technology

$$(1) \quad l_j = \frac{x_j}{\tilde{z}_j},$$

where  $l$  represents the labor resources needed to produce quantity  $x$  of variety  $j$ . Alternatively, the firm can upgrade its technology by paying a fixed adoption cost  $\lambda > 0$ . The upgraded technology is

$$(2) \quad l_j = \frac{x_j}{\tilde{\gamma}\tilde{z}_j} + \lambda,$$

<sup>4</sup> Although we do not have firm-level data, the fact that land quality varies little across space suggests the presence of substantial firm heterogeneity across corn producers.

<sup>5</sup> The monopolistic competition assumption is not necessary for the results, which would hold also in a perfectly competitive economy with heterogeneous firms as in Hopenhayn [1992].

<sup>6</sup> While our simple model solely aims at providing economic intuition, a direct map with the empirical analysis could be made by assuming that all firms within a county have the same productivity.

where  $\tilde{\gamma} > 1$ . Hence, once a firm has observed its productivity draw,  $\tilde{z}$ , it can decide whether to operate at zero fixed cost and a higher variable cost, or to upgrade to a technology with a positive fixed cost and a lower variable cost. This formulation of the adoption problem is motivated by evidence that the shift to SV seeds imposes substantial fixed costs upon producers. For example, producers must learn how to use new production practices and machinery, and incur search costs finding the SV seeds most suited to local growing conditions (Vyn [2010], Fernandez-Cornejo *et al.* [2018]).

II(ii). *Equilibrium*

We outline a partial equilibrium model assuming that wages are given and normalized to 1, and that each variety faces inverse demand

$$(3) \quad p_j = \hat{D}x_j^{\alpha-1},$$

with  $\alpha \in (0,1)$ , where  $\hat{D}$  is an exogenous demand shifter determining the market size of each firm.

In equilibrium each firm produces one variety. We therefore drop the  $j$  subscripts and indicate varieties with their productivity  $\tilde{z}$ . Firm profit maximization leads to the standard optimal pricing  $p_l(\tilde{z}) = 1/\alpha\tilde{z}$  and  $p_h(\tilde{z}) = 1/\alpha\tilde{\gamma}\tilde{z}$ , where  $i = l,h$  indicates whether the firm produces with the low or high variable cost technology after entry. Profits from using the two technologies are

$$(4) \quad \pi_l(\tilde{z}) = \left( p_l(\tilde{z}) - \frac{1}{\tilde{z}} \right) x_l(\tilde{z}) = \hat{\alpha}\hat{D}z,$$

$$(5) \quad \pi_h(\tilde{z}) = \left( p_h(\tilde{z}) - \frac{1}{\tilde{\gamma}\tilde{z}} \right) x_h(\tilde{z}) = \hat{\alpha}\hat{D}\gamma z - \lambda,$$

where  $z = \tilde{z}^{\frac{\alpha}{1-\alpha}}$ ,  $\gamma = \tilde{\gamma}^{\frac{\alpha}{1-\alpha}}$ ,  $\hat{\alpha} = (1-\alpha)\alpha^{\frac{\alpha}{1-\alpha}}$  and  $\hat{D} = D^{\frac{1}{1-\alpha}}$ . A firm with productivity  $\tilde{z}$  upgrades its technology if  $\pi_l(\tilde{z}) \leq \pi_h(\tilde{z})$ , hence the firm for which this condition holds with equality determines the technology adoption, or upgrading cutoff,  $z_h^*$ . The cutoff condition is

$$(AC) \quad z_h^* = \frac{\lambda}{\hat{\alpha}(\gamma - 1)\hat{D}}.$$

An increase in demand for any variety of corn, i.e., an increase in  $\hat{D}$ , reduces the adoption cutoff,  $z_h^*$ . The economic intuition is straightforward: a surge in demand increases the size of the market for each firm, thereby allowing more firms to cover the fixed cost of adopting the superior technology. Average industry productivity is



$$\bar{z} = \int_{z_{\min}}^{z_h^*} z f(z) dz + \gamma \int_{z_h^*}^{\infty} z f(z) dz = \frac{\kappa z_{\min}}{\kappa - 1} \left[ 1 + (\gamma - 1) \left( \frac{z_h^*}{z_{\min}} \right)^{1-\kappa} \right],$$

where  $f(z) = \kappa z_{\min}^{\kappa} z^{-\kappa-1}$  is the productivity density function. It is easy to see that as a larger share of firms adopts the new technology, the industry as a whole becomes more productive. Our simple model therefore predicts an increase in adoption of the more productive technology and an increase in average productivity following a positive demand shock. Notice that a reduction in the adoption cutoff can also be generated by a reduction in the adoption cost,  $\lambda$ .<sup>7</sup>

II(iii). *Discussion*

The model can also be used to ask whether the observed increase in productivity could be the result of more intensive use of a fixed input rather than the adoption of a more productive input. Abstracting from technology adoption, the expansion of market size,  $\hat{D}$ , could increase a revenue-based measure of productivity but not the physical/technological productivity which is the focus of our empirical analysis. Revenue-based productivity for firm  $\bar{z}$  that adopts the new technology is computed as revenues over total costs,

$$\frac{p_h(\bar{z})x_h(\bar{z})}{\frac{x_h(\bar{z})}{\bar{z}} + \lambda} = \frac{1}{\alpha + \frac{\lambda}{\alpha^{1-\alpha} \hat{D} \gamma z}}$$

Increasing a firm’s market size, through an increase in demand  $\hat{D}$  reduces the incidence of the fixed cost, thereby increasing the firm’s revenue-based productivity. Our key empirical results below, however, show that the demand shock increases physical productivity (yields and TFPQ). This implies that the observed increase in efficiency cannot be due to economies of scale coming from the more intensive use of a fixed input.

Finally, the increase in aggregate productivity in the corn industry observed in the data could be the result of a selection effect which forces the less productive firms out of the market. In Online Appendix C we show that selection effects do not play a role for observed increases in productivity. It is still useful to analyse this effect in the model. Let us assume that all firms have to pay a fixed operating cost,  $\lambda_p$ . Now the adoption cutoff is determined by  $z_h^* = (\lambda + \lambda_p) / (\hat{\alpha} (\gamma - 1) \hat{D})$ , but there is also a survival cutoff  $z^*$  below which non-adopting firms will not break even  $z^* = \lambda_p / \hat{\alpha} \hat{D}$ . It is easy to see

<sup>7</sup>Our empirical findings strongly refute the possibility that the adoption choice is generated by this supply-side channel. For example, Table A.1 shows no decrease in the cost of SV seeds during the sample period. Moreover, Figure 5 shows a strong positive correlation between the rate of SV adoption and ethanol capacity, a proxy for market size.



that an increase in demand  $\hat{D}$  decreases the survival cutoff  $z^*$ : larger market size makes survival easier. Aggregate sectoral productivity becomes

$$\bar{z} = \int_{z^*}^{z_h^*} z f(z) dz + \gamma \int_{z_h^*}^{\infty} z f(z) dz = \frac{\kappa z^*}{\kappa - 1} \left[ 1 + (\gamma - 1) \left( \frac{z_h^*}{z^*} \right)^{1-\kappa} \right],$$

where a reduction in the survival cutoff reduces aggregate productivity, thereby offsetting the positive effect of technology adoption on productivity. In our simple model, the negative selection effect indeed dominates and an increase in demand leads to a reduction in aggregate productivity. Using the two cutoff conditions we get  $z_h^* = z^*(\lambda_p + \lambda)/\lambda_p(\gamma - 1)$ , so aggregate productivity is increasing in the survival cutoff  $z^*$  and decreasing in the exogenous demand component.<sup>8</sup> Hence, this provides further theoretical support to our empirical hypothesis that technology adoption is the key force behind the increase in productivity in the corn industry.

### III. DATA

We retrieve productivity data from the National Agricultural Statistics Service (NASS) - the statistics branch of the United States Department for Agriculture (USDA). As part of its mission, the NASS 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 wheat industries within each county-industry over the period 2000 to 2007. In total the sample contains 12,344 observations, drawn from 843 counties located in the 12 states that form the Corn Belt.<sup>9</sup> 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 there. Further information on acres planted, the number of firms per acre 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

<sup>8</sup> In a more general model where an increase in market size can generate an increase in the wages of the workers in the industry, the result would be less stark, as higher wages would push the survival cutoff in the opposite direction.

<sup>9</sup> The 12 states in the sample are Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota and Wisconsin.

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 wheat 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

$$(6) \quad tfp_{ist} = y_{ist} - \alpha_k k_{ist} - \alpha_l l_{ist} - \alpha_m m_{ist} - \alpha_e e_{ist},$$

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  $\alpha_j$  ( $j \in (k, l, m, e)$ ) 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 2000 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 productivity estimation and the associated difficulty in identifying the underlying drivers of productivity growth. By using input-specific price indices 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 technology adoption is also taken from the ARMS database. This source provides annual data on the share of corn acres planted using SV seeds (the ratio of corn acres planted with SV seeds to total corn acres) for each state from 2000 onward. 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). SV seeds combine both traits. Experimental trials have consistently shown SV seeds to produce higher yields per acre by preventing destruction of the crop. However, SV seeds typically retail at a premium to single-gene seeds as shown in Online Appendix Table A.1. Both types of seed were commercially available throughout the sample period. In contrast, wheat producers only have access to single-gene variety seeds. SV wheat seeds have not yet been developed.

We match the productivity and technology adoption 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 U.S. We aggregate the plant-level data to the county level. We include only plants that use corn as a feedstock on the grounds that others are irrelevant to corn producers.

The remaining variables used in the econometric analysis are listed in Table I. This includes various types of input usage (ARMS), precipitation and extreme temperature, measured as the share of days with temperatures above the 90<sup>th</sup> percentile over the growing season (Weather Underground).<sup>10</sup> A complete description of each variable is provided in Online Appendix A.

#### IV. 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 U.S. energy policy that sparked the ethanol boom.

##### IV(i). *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]).<sup>11</sup> 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 U.S. 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 (DDG's), 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

<sup>10</sup> We match each county to the nearest weather station because not all counties contain a weather station.

<sup>11</sup> According to USDE [2013] over 90% of U.S. ethanol production relies on corn as a feedstock. Owing to differences in their chemical properties, multiple feedstocks cannot be mixed together during production. None of the ethanol plants in our sample use wheat as a feedstock.

TABLE I  
SUMMARY STATISTICS

Variable	Observations	Mean	Std. Dev.	Min	Max	Level of Aggregation	Data Source
Yield	12,344	85.30	46.12	4.50	220	County	NASS
Acres planted	12,344	8.44	4.73	0	13.04	County	NASS
Irrigation	12,344	0.05	0.18	0	1	County	NASS
Firms	12,344	0.01	0.01	0	0.16	County	NASS
Ethanol capacity	12,344	1.74	13.76	0	368	County	Authors' calculations
Exports	12,344	2.15	0.26	1.75	2.60	Industry	ARMS
Food	12,344	1.36	0.05	1.22	1.40	Industry	ARMS
Feed	12,344	5.83	0.21	5.54	6.14	Industry	ARMS
MTBE	12,344	0.09	0.28	0	1	State	EIA
Extreme temperature	12,344	0.08	0.48	0	0.14	County	Authors' calculations
Precipitation	12,344	1.10	1.45	0	8.80	County	Weather Underground
Output (ln)	12,344	15.49	1.47	8.70	18.16	County	NASS
Entry rate	12,344	0.04	0.20	0	1	State	Census
DDGs demand	12,344	0.01	0.03	0	0.66	County	NASS
Plants within 100 miles	12,344	4.66	5.37	0	34	County	Authors' calculations
Plants within 200 miles	12,344	17.24	15.82	0	81	County	Authors' calculations
Capacity within 100 miles	12,344	181	239	0	1,480	County	Authors' calculations
Capacity within 200 miles	12,344	686	623	0	3,100	County	Authors' calculations
Capacity under construction	12,344	0.04	0.18	0	1	County	Authors' calculations
Entry	12,344	0.17	0.37	0	1	County	Authors' calculations

TABLE I (CONTINUED)

Variable	Observations	Mean	Std. Dev.	Min	Max	Level of Aggregation	Data Source
TFPQ	192	0.11	0.02	0.07	0.17	State	Authors' calculations
Land and buildings	192	49.58	16.04	15.28	91.57	State	ARMS
Machinery and equipment	192	39.06	9.64	21.63	76.30	State	ARMS
Labor	192	1.81	1.07	12.35	51.47	State	ARMS
Fertilizer	192	31.50	9.09	12.35	51.47	State	ARMS
Seed cost	192	16.72	8.74	3.18	32.05	State	ARMS

shipping harvested corn from farms and co-ops to ethanol plants using lorries which are the low-cost transport option (McNew and Griffith [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.

#### IV(ii). *Legislative Changes*

The origins, of the ethanol boom lie in a series of political issues that culminated in the 2005 EP Act. During the early 2000's a perception grew within national policymaking circles that the U.S. economy was overly reliant on foreign energy supplies that were vulnerable to interruption (Diggs [2012]). In response to these pressures, the EP Act 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 EP Act mandated a rise in the ethanol content of gasoline from 4 billion gallons in 2006 to 7.5 billion in 2012. In addition, the EP Act set a target, known as the Renewable Fuel Standard (RFS), that a minimum 10% of gasoline should be made up of ethanol in future.<sup>12</sup> The subsequent Energy Independence and Security Act of 2007 set yet higher targets, mandating a minimum 36 billion gallon ethanol content by 2022.

#### IV(iii). *The Ethanol Boom*

The volumetric ethanol production targets and the RFS guaranteed ethanol demand. Ethanol producers also benefited 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<sup>3</sup> levied on imported ethanol.<sup>13</sup> Because vehicles did not require engine modifications to run on blended ethanol, most gasoline retailers throughout the U.S. 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.<sup>14</sup> Following successful engine performance tests, the U.S. Environmental Protection Agency

<sup>12</sup>The USDA Feed Grains Database reports that by 2009 the ethanol market share of the U.S. gasoline industry had reached 8% as a result of the energy legislation.

<sup>13</sup>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.

<sup>14</sup>Sales of e85-engine vehicles account for between 33% and 40% of annual auto sales during the sample period. In 2000 approximately 2.2 million e85 vehicles were sold compared to 2.8 million in 2007.

TABLE II  
ETHANOL INDUSTRY EVOLUTION

Year	Plants	Net Entry (%)	Capacity (mgy)	Multiplant (%)
2002	56		2,240	15
2003	62	10.71	2,505	11
2004	72	16.13	2,948	10
2005	81	12.50	3,473	10
2006	107	32.10	4,052	12
2007	151	41.12	5,022	10

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

authorized the use of blended gasoline in all motorcycles, heavy duty vehicles and non-road engines.

Online Appendix Figure A.1 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 II provides further detail on these patterns. Between 2002 and 2007 the number of ethanol plants increased from 56 to 151 and capacity increased by almost 225%. Much of this entry occurred in the two years after implementation of the EP Act when the net entry rate spiked to 32% and 41%. 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 57 mgy in 2007), reflecting the entry of larger plants and capacity expansions.<sup>15</sup>

Figure 1 documents the increasing importance of the ethanol sector as a source of the demand for corn following enactment of the EP Act. 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 25% by 2007 and 40% in 2010. In addition, Online Appendix Figure A.3 shows that the increase in ethanol demand did not displace other sources of corn demand such that demand for corn was strictly higher after 2005.

## V. EMPIRICAL METHODOLOGY AND RESULTS

### V(i). *Identification Strategy*

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

<sup>15</sup> 3.5 billion gallons of ethanol were contained in gasoline in 2004, compared to 13.3 billion gallons in 2010. Online Appendix Figure A.2 shows that the market share of ethanol imports is close to 0 in all years.



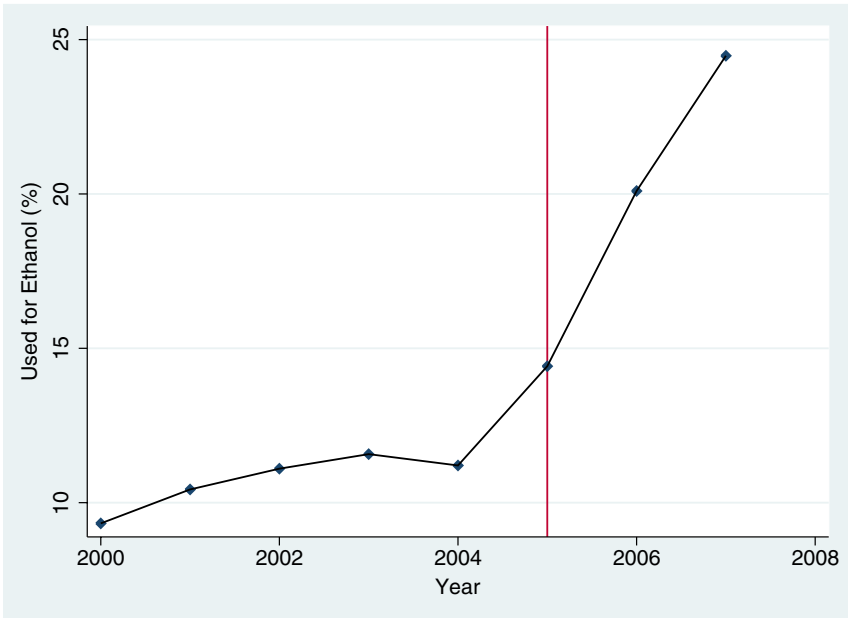


Figure 1

Share of U.S. 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 EP Act was signed into law. [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

$$(7) \quad y_{ict} = \alpha_{ic} + \beta \text{Corn}_{ic} * \text{Post}_t + \delta X_{ict} + \gamma_{ct} + \varepsilon_{ict},$$

where  $y_{ict}$  is an outcome variable (productivity or TFPQ) in industry  $i$  in region  $c$  (either a county or state) at time  $t$ ;  $\text{Corn}_{ic}$  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,  $\text{Post}_t$ , which is equal to 1 for the years 2005–2007 when the EP Act is in force, 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  $\varepsilon_{ict}$  is the error term. We also include a set of region-year ( $\gamma_{ct}$ ) and region-industry ( $\alpha_{ic}$ ) dummy variables to eliminate unobserved heterogeneity. In the yield (TFPQ) tests the region is defined as a county (state). Region-year effects capture

all time-varying productivity 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 determinants that are region specific, but differentially affect the dependent variable within the treatment and control groups, we include region-industry effects. We cluster the standard errors at the region level in line with Bertrand *et al.* [2005].

Central to this approach is establishing an implied counterfactual. We choose the wheat industry because it is ubiquitous throughout the Corn Belt, uses a similar production process to corn and is planted and harvested at the same time as corn meaning that it is subject to similar climatic conditions over the growing season. Wheat, like corn, can in principle be used to produce ethanol. However, this use is very small in the aggregate. Wheat is not used as an input by the ethanol producers in our sample and there is evidence that converting ethanol plants to use wheat as a feedstock is unlikely. According to the Environmental Protection Agency, 0.4% of total U.S. ethanol production is made from wheat and milo grains. Industry sources state that U.S. ethanol producers do not switch to using wheat for ethanol owing to 1) the process of retrofitting plants to grind wheat instead of corn is costly, 2) ethanol yields from wheat are 20-30% lower compared to the same weight of corn, and 3) wheat does not produce the distillers dry grains that are sold by ethanol producers as an additional source of revenue.

The key identifying assumption underlying our tests is the parallel trends assumption. Figure 2 plots productivity in the corn and wheat industries during the sample period. Before 2005, productivity evolves in a very similar way within both industries. The parallel trends assumption therefore holds. However, after 2005 productivity in the corn industry begins to increase whereas wheat productivity does not.

Difference-in-difference estimates are more convincing when the treatment and control groups are similar *ex ante*. We therefore use t-tests to examine the similarity of the production process (measured using inputs per acre) during the pre-treatment period. Table III shows we cannot reject the null of equality in the per acre value of land and buildings, machinery, labor, fertilizer and seed inputs. Together these pieces of evidence suggest that wheat is a valid counterfactual.<sup>16</sup>

<sup>16</sup> An implicit identifying assumption is that when deciding on where to plant corn and wheat, farmers do not switch wheat to inferior land to make way for corn. If this assumption fails, then the productivity of wheat may fall. We cannot definitively rule out this possibility. However, two pieces of evidence suggest this was not the case and that wheat productivity was similar before and after the EP Act. First, Figure 4 shows a high degree of overlap in the distribution of wheat productivity in 2000 and 2007. Second, using data from the wheat industry we estimated the equation  $yield_{ct} = \alpha Post2005_t + \beta X_{ct} + \gamma_c + \varepsilon_{ct}$ , where  $yield_{ct}$  is the natural logarithm of wheat productivity in county  $c$  during year  $t$ ,  $Post2005_t$  is a dummy variable equal to 1 for the years 2005, 2006 and 2007, 0 otherwise,  $X_{ct}$  is the vector of controls,  $\gamma_c$  denote county fixed effects, and  $\varepsilon_{ct}$  is the error term.  $\beta$  indicates the change in wheat productivity between the pre and post-EP Act periods within counties. We estimate  $\beta$  to be 0.0111 (t-statistic = 1.09). The insignificant coefficient suggests there was little change in wheat productivity between the periods.



Figure 2  
Productivity Evolution

*Notes:* This figure plots yield per acre in natural logarithms in the corn and wheat industries during the sample period. The vertical line represents the beginning of 2005, the year when the EP Act was signed into law. [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

TABLE III  
PRE-TREATMENT GROUP COMPARISONS

Variable	Corn	Wheat	Diff.	Std. Error	<i>t</i> -stat
Land and buildings	52.75	50.74	-1.80	5.76	-0.32
Machinery	39.45	39.77	0.32	2.52	0.06
Labor	1.84	1.63	-0.22	0.33	-0.66
Fertilizer	31.69	29.84	-1.85	5.11	-0.36
Seed	32.40	30.16	-2.24	1.61	1.39

*Notes:* This table presents the results of *t*-tests on the equality of input expenditure per acre between the corn and wheat industries during 2000 to 2004.

#### V(ii). *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 2007 when the demand shock has taken effect. There is a clear

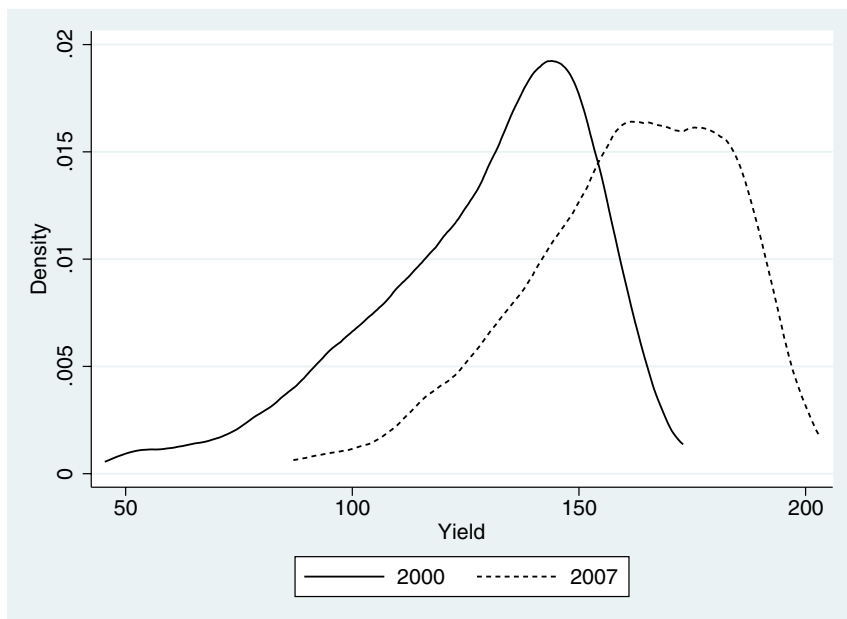


Figure 3

## Corn 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 2007. [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

unambiguous increase in average industry productivity with a large rightward shift in the survival productivity threshold.<sup>17</sup> In contrast, Figure 4 shows wheat productivity did not respond to the demand shock. Online Appendix Figure A.5 provides clear evidence across all states in the sample that the passing of the EP Act coincides with the steep section of the familiar S-shaped technology adoption function. The evidence reported in Figure 5 affirms that demand conditions lie at the heart of our findings. Specifically, the figure illustrates that technology adoption is positively correlated with increases in local ethanol capacity, a strong proxy for demand.<sup>18</sup>

Turning to econometric methods, Table IV reports estimates of Equation (7) that provide evidence that the demand shock caused a significant increase in productivity within the corn industry. Column 1 of Table IV reports estimates from a simple difference-in-difference model based on Equation (7)

<sup>17</sup> Figure A.4 in the Online Appendix reports the distribution of productivity in 2000 and 2007 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.

<sup>18</sup> The correlation is also highly statistically significant. Correlation = 0.40 (p-value = 0.00).

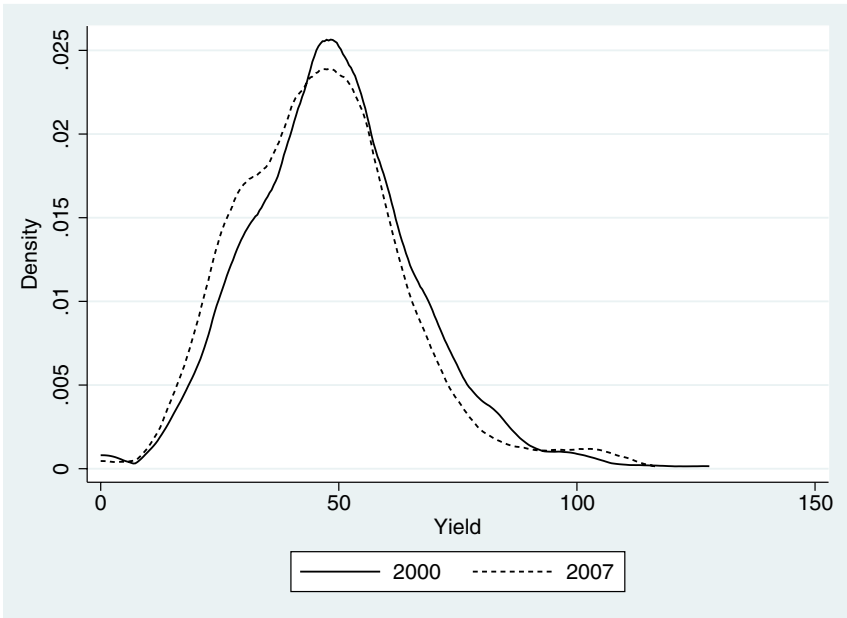


Figure 4  
Wheat Productivity during the Sample Period

*Notes:* This figure shows kernel density plots the distribution of yield per acre in the wheat industry in 2000 and 2007. [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

without any control variables. The effect is economically meaningful and highly statistically significant. The ATE is estimated to be equivalent to a 7.6% increase in productivity.

In column 2 of Table IV we add as controls the number of acres planted, the incidence of irrigation technologies and the number of operating firms. 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. We find that the correlation is both negative and statistically significant. The irrigation coefficient is estimated to be statistically insignificant. The number of firms per acre captures competitive effects. Consistent with this intuition we find a 10% increase in the number of firms is associated with a 0.47% increase in yield. The addition of these controls does little to alter the estimated effect of the EP Act on yield per acre.

Central to the empirical strategy is the claim that the demand shock was due to the expansion of the ethanol industry. To verify that changes in market size drive our inferences, we interact the corn dummy variable with the ethanol

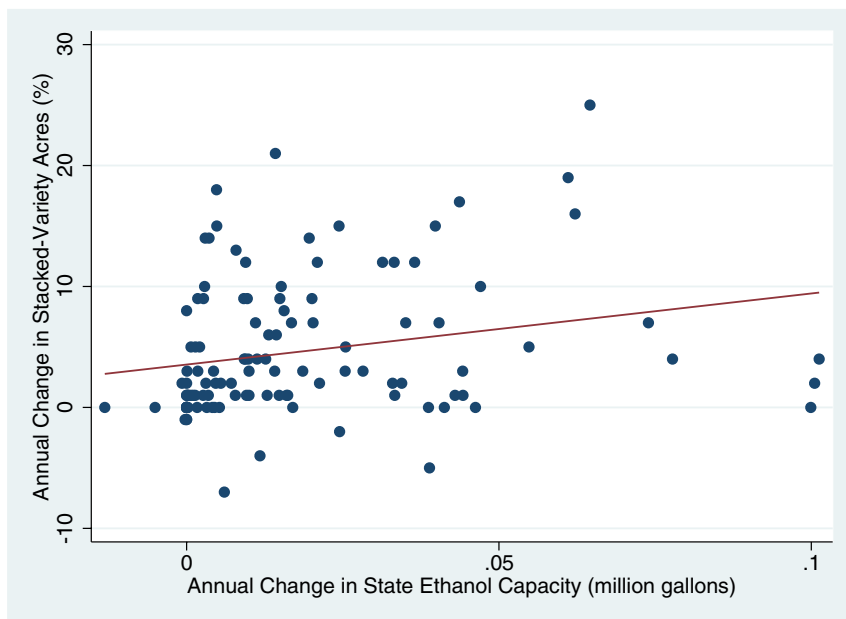


Figure 5  
Ethanol Demand and Technical Change

*Notes:* This figure plots the annual change in the share of corn acres planted with SV seeds against the annual change in ethanol capacity in each state. [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

capacity variable.<sup>19</sup> The estimates in column 3 of Table IV show that a 10% increase in local ethanol capacity causes a 0.5% increase in corn productivity. Considering ethanol operating capacity for the average county increased from 455 mg in 2004 to 1,040 mg in 2007, the estimates imply demand from the ethanol industry provoked an 11.9% productivity increase.<sup>20</sup>

In columns 4 and 5 of Table IV we present evidence from regressions in which TFPQ is the dependent variable in equation (7). Here we find that the demand shock had a smaller effect, an increase of 0.78%. The smaller 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 TFPQ is small

<sup>19</sup> Evidence 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 mg 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.

<sup>20</sup> This finding is robust to defining the local market using a 100 mile radius.

TABLE IV  
THE EFFECT OF DEMAND ON PRODUCTIVITY

Regression no.	1	2	3	4	5	6	7
Dependent variable	Yield	Yield	Yield	TFPQ	TFPQ	Yield	Yield
Corn * Post	0.0735*** (10.62)	0.0674*** (8.87)	0.0078*** (5.92)	0.0078*** (5.92)	0.0086* (2.28)	0.0052*** (8.01)	0.0052*** (8.01)
Acres planted		-0.0825*** (-5.71)	-0.0643*** (-4.64)	0.0051 (1.49)	0.0086* (2.28)	-0.0780*** (-5.58)	-0.0623*** (-4.10)
Irrigation		0.0009 (0.20)	0.0007 (0.17)	-0.0121 (-1.71)	-0.0245** (-3.59)	0.0018 (0.43)	0.0018 (0.41)
Firms		0.0468*** (4.87)	0.0648*** (6.12)	-0.0007 (-0.66)	0.0013 (0.64)	0.0415*** (4.34)	0.0562*** (5.18)
Corn * Ethanol capacity			0.0520** (2.48)		0.0010*** (4.17)		
Corn * SV share						0.0933*** (11.95)	0.0731*** (6.41)
Corn * Post * SV share							0.1398*** (8.11)
County-year FE	Yes	Yes	Yes	No	No	Yes	Yes
County-industry FE	Yes	Yes	Yes	No	No	Yes	Yes
State-year FE	No	No	No	Yes	Yes	No	No
State-industry FE	No	No	No	Yes	Yes	No	No
Observations	12,344	12,344	12,344	192	192	12,344	12,344
R <sup>2</sup>	0.94	0.94	0.94	0.99	0.99	0.94	0.94

Notes: County-level data are used in regressions 1-3, 6 and 7. State-level data are used in all other columns. DD denotes difference-in-difference. IV-FS represents IV first-stage. IV-SS denotes IV second-stage. The standard errors are clustered at the county level in all regressions except in columns 4, 5, 8 and 9 where they are clustered at the state level. *t*-statistics are reported in parentheses. \*\*\*, \*\*, \* and \* denote significance at the 1%, 5% and 10% levels.



because SV seeds are more expensive than single-gene seeds. The agricultural economics literature discusses other sources of productivity gains that have followed from experience in using SV 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, lower gasoline costs, and higher TFPQ.

The remaining columns in Table IV tie the observed productivity gains to the adoption of SV seed. We first approach this question by including an interaction between the corn dummy variable and the share of acres planted with SV seed in Equation (7). The estimates in column 6 show a significant positive relationship between the adoption of SV seeds and productivity within the corn industry. A 10% increase in the incidence of SV seed is estimated to increase corn productivity by 0.93%.

Intuitively, one would anticipate the effects of the SV seed technology to be more pronounced among corn producers where adoption rates are high-est. We therefore estimate a triple-difference model

$$(8) \quad y_{ict} = \alpha_{ic} + \beta_1 \text{Corn}_{ic} * \text{Post}_t + \beta_2 \text{Corn}_{ic} * \text{SVseed}_{ct} \\ + \beta_3 \text{Corn}_{ic} * \text{Post}_t * \text{SVseed}_{ct} + \delta X_{ict} + \gamma_{ct} + \varepsilon_{ict},$$

where all variables are defined as before except  $\text{SVseed}_{ct}$  which is the share of acres planted with SV seed in each state-year.

The results of Equation (8) are reported in column 7 of Table IV. The Corn-Post interaction coefficient remains positive and statistically significant but is economically smaller compared to previous specifications. However, this is consistent with the Corn-SV seed and Corn-Post-SV seed interactions that are highly statistically significant and economically important. In essence, the post 2005 increase in corn productivity is driven by technology adoption. The triple interaction coefficient indicates that within the corn industry, productivity increased relatively more post 2005 in areas that adopted the SV seed technology to a greater extent.<sup>21</sup> Hence, adoption of the new technology underlies the productivity gains we observe following the demand shock.<sup>22</sup>

<sup>21</sup> USDA field trials show that stacked-variety corn seeds produce 171 bushels per acre versus 134 for single-gene seeds. By the end of our sample period stacked varieties accounted for approximately 25% of acres planted. This implies a productivity increase of 9.25 bushels per acre. Consistent with this, the 7% ATE we estimate is equivalent to a 9.38 bushel per acre increase in productivity.

<sup>22</sup> In the model, technology adoption involves sunk costs. An alternative explanation could be that adoption is a function of prices and the value of variable investments. In that case, one would expect to observe a reduction in the incidence of the stacked-variety technology as prices fall following contractions in demand. On the other hand, if the sunk cost assumption is correct, the incidence of the technology would be invariant to price changes. This is indeed the case. The data show that relative to prices in 2008, corn prices fell in 2009 and 2010. This was not accompanied by a fall in the incidence of stacked varieties. In 2008 50% of acres were planted using stacked variety seeds compared to 54.1% in 2009 and 55.7% in 2010. The incidence of the technology also does not decline after 2013 when corn prices fell dramatically.

## VI. THREATS TO IDENTIFICATION

Before concluding that demand shocks improve productivity causally, we rule out potential confounding influences. In our setting, the main concern 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 EP Act and differentially affect the corn and wheat industries. We therefore review a series of events that occur throughout our sample period and empirically establish whether they confound our inferences.

VI(i). *Inputs and Technology Costs*

An obvious confound could be that corn producers increased other factor inputs rather than adopting SV seeds to raise yields. The evidence in columns 1 to 5 of Table V indicates that this was not the case. Specifically, using Equation (7) we find no evidence of a significant change in the per acre capital stock, labor, fertilizer or the incidence of productivity-enhancing irrigation technologies within the corn sector post 2005.

In column 6, we explore whether the technical change we observe in the data was due to a reduction in seed costs. 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 6 of Table V indicate this was not the case. Rather, there are no differential trends in seed costs between the treatment and control groups post 2005. The descriptive evidence in Online Appendix Table A.1 also refutes that falling technology costs drive the results. Specifically, it shows that the real cost of SV seeds increased strongly through the sample period.<sup>23</sup>

VI(ii). *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

<sup>23</sup> One could argue that the main barrier to technology adoption was societal attitudes towards GE technology. For example, consumers may be hesitant about purchasing food produced using GE seeds. The demand shock may have alleviated this constraint because farmers could use SV seeds to supply the ethanol industry. This argument is implausible for two reasons. First, SV 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 50% of planted acres used stacked-varieties despite ethanol's accounting for 35% 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.

TABLE V  
INPUT USAGE AND TECHNOLOGY COSTS

Regression no.	1	2	3	4	5	6
Dependent variable	Land & buildings	Mach & equip	Labor	Fertilizer	Irrigation	Seed
Corn * Post	-0.0239 (-0.90)	0.0273 (0.42)	0.0107 (0.09)	0.0050 (0.18)	0.0064 (0.17)	0.0230 (1.09)
State-year effects	Yes	Yes	Yes	Yes	No	Yes
State-industry effects	Yes	Yes	Yes	Yes	No	Yes
County-year effects	No	No	No	No	Yes	No
County-industry effects	No	No	No	No	Yes	No
Observations	192	192	192	192	12,404	192
R <sup>2</sup>	0.99	0.94	0.94	0.99	0.96	0.99

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.

TABLE VI  
ROBUSTNESS TESTS

Regression no.	1	2	3	4	5	6	7	8	9
Sample	Texas								
Corn * Post	-0.0313 (-1.35)		0.0745*** (8.48)	0.0635*** (8.39)	0.0593*** (7.96)	0.0674*** (7.70)	0.0673*** (8.86)	0.0319*** (6.43)	0.0759*** (6.71)
Corn * Placebo		0.0060 (0.44)							
Corn * Exports			0.1569*** (3.84)						
Corn * Feed				0.1889*** (10.90)					
Corn * Food					-0.9984*** (-14.04)				
Corn * MTBE						0.0843*** (4.99)			
Corn * Extreme temperature							0.0189 (1.43)		
Corn * Precipitation								0.0327*** (8.25)	
Corn * Firms									-0.1875*** (87.74)

TABLE VI (CONTINUED)

Regression no.	1	2	3	4	5	6	7	8	9
Sample	Texas								
	Corn Belt								
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	822	7,814	12,344	12,344	12,344	12,344	12,344	12,344	12,344
R <sup>2</sup>	0.97	0.94	0.94	0.95	0.95	0.94	0.94	0.34	0.69

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.

tests. We leverage the fact that corn is produced in Texas but producers there did not experience a change in demand after 2005.<sup>24</sup> Given that operating conditions in Texas are similar to the Corn Belt but the ethanol industry is essentially absent, 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. When we use the Texan sample in column 1 of Table VI, the Corn-Post interaction coefficient is statistically insignificant. The key message from this test is that productivity only increased in corn-producing areas that were exposed to the demand shock.

Our second falsification test rules out that diverging pre-treatment productivity trends or anticipation effects drive our findings. We restrict the sample period to 2000 to 2004 and generate a placebo treatment dummy variable that takes the value of 1 from 2002 onward, 0 otherwise. We then interact the Corn and Placebo dummy variables. The results of this test in column 2 of Table VI show the placebo interaction is statistically insignificant. Hence, corn producers did not anticipate the EP Act. Corn productivity only increased following the demand shock.

#### VI(iii). *Other Demand Shocks*

Clean identification requires that there were no coinciding changes in demand for corn from other sources following implementation of the EP Act. 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 VI. Despite controlling for differential shocks to export, food and feed demand, the Corn-Post coefficient remains positive, statistically significant and comparable in magnitude to the baseline results.

Another potential concern is that the EP Act 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 MTBE

<sup>24</sup> 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. Corn producers in Texas were unaffected by the ethanol boom because high transport costs make it unfeasible to sell corn to distant ethanol plants in the Corn Belt. Historically, ethanol producers chose not to locate in Texas due to the absence of state-level biofuel incentives, and because ethanol was not used as a gasoline oxygenate.

producers may explain the limited response of ethanol producers. It was only later, in 2006, when 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 variable, 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 VI show that our main findings are robust to this change. Interestingly, the Corn-MTBE coefficient is positive and statistically significant. Given that the MTBE demand shock was due to exogenous health concerns this permanently reinforced corn demand. The findings therefore provide further support that increasing demand leads to productivity improvements.

#### VI(iv). *Additional Robustness Tests*

Next, we consider whether climatic shocks drive our inferences. The results in columns 7 and 8 of Table VI show that extreme temperature shocks and precipitation do not confound the effect of demand on productivity, respectively.

A further concern is that there might have been spillover effects on the control group through general equilibrium effects. If so, the ATE's would be spurious due to contamination of the implied counterfactual. To tackle this issue we first use alternative control groups. Column 1 of Online 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 wheat it cannot be used to produce ethanol. Despite the change in counterfactual, we continue to reach the same conclusion as before.

The second procedure we adopt uses Monte Carlo simulations to test whether wheat productivity was directly affected by the EP Act. To implement this test we use the county-level wheat productivity data over 2000 to 2007. We randomly assign 50% of counties to placebo treatment status and the rest to control status. The placebo treatment dummy is set equal to 1 for the years 2005 to 2007, and 0 otherwise. We then estimate the equation

$$(9) \quad yield_{it} = \alpha_i + \beta placebo_{it} + \gamma_t + \varepsilon_{it},$$

and repeat the procedure 1,000 times. As these regressions focus only on observations from the wheat industry, they provide an indication of whether conditional on year effects, wheat yields within the county were significantly higher during the EP Act period compared to before. Given that demand for wheat did not change we would expect the placebo treatment dummy variable to be rejected only by chance. The rejection rates reported in Online Appendix Table A.4 Panel A are consistent with this view, and indicate no spillover effects.

Next, we investigate whether reallocation of market share explains our findings. In Online Appendix C we use the procedures outlined by Olley and



TABLE VII  
LOBBYING TESTS

	Pre-2005	Post-2005	Difference
Corn	0.0400	0.1224	0.0824
Wheat	0.1160	0.1185	-0.0025
Difference-in-difference			0.0849
			(1.67)

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

Pakes [1996] and Combes *et al.* [2012] to examine the between and within-counties effect of the demand shock on productivity growth. The evidence in Online Appendix Table A.5 rejects the view that reallocation of market shares across firms in different counties drives our findings. This result is consistent with the theory we outline below where the within effect is the driver of productivity improvements.

Finally, we examine whether our findings are driven by pro-competitive effects of changes in demand. We interact the corn dummy with the number of firms variable and report the estimates in column 9 of Table VI. Our key finding endures.

#### VI(v). *Endogeneity of the EP Act and Ethanol Capacity*

One could argue that lobbying affected the timing of the EP Act. 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 Online 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 2000 and 2005 but increase thereafter. Hence, neither corn nor ethanol producers influenced the timing of the EP Act 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 VII also produce no evidence of significant differences in lobbying contributions by the treatment and control groups post 2005.<sup>25</sup>

<sup>25</sup> One could argue that the EP Act 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 two reasons. First, there is not a single mention of the word 'corn' in the EP Act 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 EP Act. This result holds when we expand the sample to include earlier years as well.

It is clear from Online 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 plants' 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-EP Act 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 DDG's as an animal feed (McAloon *et al.* [2000]).<sup>26</sup> 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

$$(10) \quad y_{ct} = \gamma_c + \beta_1 Yield_{ct-1} + \beta_2 Yield_{ct-2} + \beta_3 Output_{ct} + \beta_4 DDG_{ct} + \beta_5 Competitors_{ct} + \gamma_t + \varepsilon_{ct},$$

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 DDG's proxied by the number of cattle on feed within a 50 mile radius of the county centroid. DDG's are the principal by-product of ethanol production that can be used as a feedstock for farm animals. They are an important determinant 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

<sup>26</sup> 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 U.S. counties contain one or no ethanol plants. This is consistent with evidence from McNew and Griffith [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 VIII  
EXOGENEITY TESTS

Regression no.	1	2	3	4	5	6	7	8	9	10
	Entry			Capacity under construction						
Yield	0.0000 (0.42)	0.0000 (0.07)	0.0000 (0.07)	0.0000 (0.06)	0.0000 (0.16)	0.0000 (0.03)	-0.0001 (-0.41)	-0.0001 (-0.58)	-0.0000 (-0.27)	-0.0000 (-0.17)
Output		-0.0057 (-0.31)	-0.0059 (-0.32)	-0.0014 (-0.11)	-0.0008 (-0.07)		0.0030 (0.35)	0.0057 (0.68)	-0.0017 (-0.28)	-0.0011 (-0.18)
Plants within 100 miles		-0.0038* (-1.87)					-0.0061*** (-2.73)			
Plants within 200 miles			-0.0010 (-1.19)					-0.0026*** (-2.95)		
DDG's demand		0.7300* (1.78)	0.7796* (1.75)	0.7831* (1.74)	0.8067* (1.79)		0.7158* (1.81)	0.6711* (1.73)	0.6552* (1.19)	0.6640* (1.22)
Capacity within 100 miles				-0.0001*** (-2.73)					-0.0001** (-2.22)	
Capacity within 200 miles					-0.0000** (-2.49)					-0.0000** (-2.16)
Observations	7,524	7,524	7,524	7,524	7,524	7,524	7,524	7,524	7,524	7,524
R <sup>2</sup>	0.81	0.31	0.31	0.81	0.81	0.28	0.28	0.28	0.28	0.28

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.

location of new ethanol plants found elsewhere in the literature. A full set of county  $\gamma_c$  and year  $\gamma_t$  dummies are also included in the model.  $\epsilon_{ct}$  is the error term. We estimate Equation (10) using a linear probability model due to the inconsistency of fixed-effect probit models.

The results of these tests are provided in Table VIII. There are three key findings, all of which are similar to evidence already found in the literature. 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 DDG markets, although the coefficient estimate is only significant at the 10% level.

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 DDG demand and capacity under construction. The size and location of ethanol plants appear therefore, to be unrelated to productivity in the corn sector.

## VII. CONCLUSIONS

In this paper we analyze the link between market size, technology adoption and productivity by exploiting exogenous variation in the demand for corn following modifications to U.S. energy policy which triggered a sharp increase in ethanol production, a key downstream industry for corn. Using difference-in-difference estimations that leverage the fact that wheat is grown in close proximity to corn but is not used to manufacture ethanol we find robust evidence that increases in demand cause firms to adopt more efficient technologies (higher quality genetically modified seeds) leading to productivity improvements. Economically, we find that the demand shock led physical productivity to increase by approximately 7% within the treatment group. Triple-difference models show that within the corn industry, the extent of the productivity gains following the demand shock were larger in areas with a higher incidence of technology adoption.

We also propose a simple model where heterogeneous firms can pay a fixed cost to obtain a more sophisticated technology which allows them to produce at lower variable costs. The theory suggests that larger demand leads to a higher share of firms' adopting the better technology and, as a consequence, to higher aggregate productivity. In the absence of technology adoption an increase in firms' market size generates a reduction in average productivity as larger demand allows less productive firms to survive. Revenue-based productivity can

still potentially increase because of a more intense use of any fixed factor, but abstracting from technology adoption a larger market does not lead to higher physical/technological efficiency. Our results provide new, much needed evidence, and some additional insights on the important role that demand plays in motivating technology adoption and productivity improvements.

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